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Neighborhood Environment and Type 2 Diabetes Comorbidity in Serious Mental Illness

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Keywords

environment, neighborhood, illness, serious, mental, comorbidity, diabetes, 2, type

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Neighborhood Environment and Type 2 Diabetes Comorbidity in Serious Mental Illness

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Abstract

Aim: The aim of this study was to examine the association between neighborhood characteristics and type 2 diabetes (T2D) comorbidity in serious mental illness (SMI). We investigated associations of neighborhood-level crime, accessibility to health care services, availability of green spaces, neighborhood obesity, and fast food availability with SMI-T2D comorbidity. **Method:** A series of multilevel logistic regression models accounting for neighborhood-level clustering were used to examine the associations between 5 neighborhood variables and SMI-T2D comorbidity, sequentially adjusting for individual-level variables and neighborhood-level socioeconomic disadvantage. **Results:** Individuals with SMI residing in areas with higher crime rates per 1000 population had 2.5 times increased odds of reporting T2D comorbidity compared to the individuals with SMI residing in lower crime rate areas after controlling for individual and areal level factors (95% CI 0.91-6.74). There was no evidence of association between SMI-T2D comorbidity and other neighborhood variables investigated. **Conclusion:** Public health strategies to reduce SMI-T2D comorbidity might benefit by targeting on individuals with SMI living in high-crime neighborhoods. Future research incorporating longitudinal designs and/or mediation analysis are warranted to fully elucidate the mechanisms of association between neighborhoods and SMI-T2D comorbidity.

Keywords

serious mental illness, type 2 diabetes, neighborhood characteristics

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Introduction

Research literature reports a type 2 diabetes (T2D) prevalence rate of approximately 13% in populations with serious mental illnesses (SMI) such as schizophrenia, bipolar disorder, or major depression.[1] This represents a 2 to 4 fold increase in risk compared with the general population.[1,2] Both SMI and T2D contribute significant individual and public health burdens when present independently, and are the 2 leading causes of morbidity worldwide.[3] The comorbidity compounds this burden by worsening the outcomes for each condition.[4] Type 2 diabetes comorbidity in SMI is associated with several adverse consequences such as increased mortality; reduced life expectancy of up to 30 years; worse cognitive decline; poor clinical and functional outcomes; higher health care costs; and reduced quality of life for people with mental illness.[2,5,6]

Neighborhood characteristics have been extensively linked to traditional risk factors of T2D such as physical inactivity, poor-quality diet, stress, and obesity.[7-11] Some studies have also investigated more specific features of neighborhood environments in relation to T2D risk. For example, reports from the Multiethnic Study of Atherosclerosis indicated that living in a neighborhood with better resources for physical activity and healthy food was associated with

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lower prevalence of insulin resistance[12] and lower incidence of T2D.[10,13] Sundquist et al[14] reported negative associations between neighborhood built environmental features and T2D risk in a large sample of Swedish adults. Studies from Australia have reported significantly lower incidence of T2D in greener neighborhoods after controlling for sociodemographic factors.[15,16] Neighborhood social features such as safety and crime were also found to be associated with conditions related to diabetes such as obesity, reduced physical activity, and psychological distress.[17-19] Neighborhood characteristics have also been associated with SMI.[20-24] Neighborhood-level research on SMI has investigated a wide range of features, including accessibility of health services,[21] availability of green spaces,[25] presence of tobacco and alcohol vendors,[23] social capital, and social disorder.[24]

Few studies have explored the association between neighborhood characteristics and T2D comorbidity in SMI, despite the public health burden and the plausibility of such associations.[26] Individuals with SMI are more likely to live in and be exposed to neighborhood environments that exacerbate T2D risk such as higher concentration of fast food outlets, lack of health care resources, and unsafe environments due to their lower socioeconomic status.[27,28] These contextual features may compound the experiences of psychosocial stress and encourage participation in adverse health behaviors such as unhealthy eating, physical inactivity, and excess weight gain, all of which can contribute to T2D risk.[18,27] We recently reported a statistically significant association between SMI-T2D comorbidity and neighborhood-level socioeconomic disadvantage.[29] One of the plausible explanations for the higher SMI-T2D comorbidity risk in disadvantaged neighborhoods may be the disproportionate availability of neighborhood resources in more disadvantaged neighborhoods as posited by the social determinants of health model.[30] For example, disadvantaged neighborhoods may lack access to fresh produce and be dominated by fast food and convenience stores, making the latter the easily available food option.[31] Similarly, disadvantaged neighborhoods might lack an environment conducive to physical activity.[1] Further exploration and identification of specific neighborhood-level characteristics is required to advance our understanding of T2D comorbidity in SMI and the possible associations neighborhood environments might have with this comorbidity. Understanding these associations may also help us develop integrated policies or place-based interventions that promote healthier environments to reduce the higher burden of T2D in individuals with SMI. There is, however, little evidence in the peer reviewed literature regarding the implementation and evaluation of such neighborhood-level integrated strategies on individuals with mental illness.

In this study, we aimed to investigate the associations of neighborhood environments with T2D comorbidity in individuals with SMI. A number of neighborhood indicators of T2D risk previously identified in the literature were analyzed. We specifically proposed to examine the association of 5 contextual neighborhood factors with SMI-T2D comorbidity: (1) neighborhood-level crime, (2) access to health care services, (3) availability of green spaces, (4) availability of fast food outlets, and (5) neighborhood-level obesity.[1,7,15,18,32-34]

Methodology

Study Design and Setting

This cross-sectional, multilevel study was conducted in Illawarra and Shoalhaven regions of New South Wales (NSW), Australia. The study site encompassed 4 local government areas of Kiama, Shellharbour, Shoalhaven, and Wollongong, and had an estimated resident population of 368 604 people at the time of the 2011 Australian Census of Population and Housing.[35] State suburbs were used as proxies for neighborhoods in this study as it was the smallest unit at which outcome data were available. State suburbs are the Australian Bureau of Statistics (ABS) approximation of suburbs gazetted by the Geographical Names Board of NSW.[36] The Illawarra-Shoalhaven region is composed of 167 suburbs with an average population of 2207 residents in 2011.[35] The University of Wollongong and Illawarra Shoalhaven Local Health District Human Research Ethics Committee granted ethical approval for this study (protocol number 2017/428).

Individual-Level Data and the Outcome variable

The individual-level data utilized in this study were extracted from the Illawarra Health Information Platform (IHIP), a research partnership established between Illawarra Shoalhaven Local Health District (ISLHD) and University of Wollongong for providing de-identified ISLHD data to researchers. Data extraction was based on the International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modification (ICD-10-AM), and covered the period from 2010 to 2017. Eligibility criteria required a primary or additional diagnosis of schizophrenia (F20), other nonaffective psychosis (F22-F29), bipolar disorder (F30, F31), major depression (F32, F33) or other affective disorders (F34, F39) in the inpatient records of ISLHD. The outcome variable was SMI-T2D comorbidity, which was defined as having a T2D principal or stay diagnosis (E11) in people with SMI. Comorbidity details were extracted as either present or absent along with each record with an SMI diagnosis. We restricted our analysis to individuals with SMI who were 18 years and over. Individuals were excluded from the analysis if they lived outside the Illawarra-Shoalhaven (n = 50) or had missing information (n = 291). Consequently, the final sample consisted of 3816 individuals with a diagnosis of SMI, of whom 463 (12.3 %) had a T2D comorbidity.

Neighborhood-Level Data

Our study focused on 5 neighborhood-level variables: (1) neighborhood-level crime, (2) access to health care services, (3) neighborhood-level obesity, (4) availability of green spaces, and (5) availability of fast food outlets. The selection of explanatory variables included in this analysis was somewhat restricted by data availability. Obesity was used as a contextual variable in this analysis as the information on individual-level obesity was not available for the study sample. Moreover, neighborhood environments are reported to provide cues that support social norms defining individuals' healthy behaviors, which can be compromised in a higher obese neighborhoods.[37] Hence the contextual effect of neighborhood level obesity may be informative in determining the T2D risk in SMI.

Annual area-level crime counts were obtained from the NSW Bureau of Crime Statistics and Research for the period 2010 to 2017. Crime types considered were nondomestic violent assaults, homicides, malicious damage to properties, abduction and kidnapping, robbery, and theft. Crime counts per neighborhood were expressed as rates per 1000 people using estimated resident populations from the 2011 Australian Census of Population and Housing.[35] Health care services data were extracted from the National Health Service Directory (NHSD) available from the Australian Urban Research Infrastructure Network (AURIN) portal for the year 2016.[38] To assess the availability of primary care, hospital, and mental health services in Illawarra-Shoalhaven, we used the 2-step floating catchment area method (2FSCA) that explicitly considers health care service supply and population demands and their interactions within a catchment.[39] In the first step, a 15-km distance catchment, corresponding to 30 minutes of travel time[40] was placed around each health care service provider, and a provider to population ratio was computed and assigned to these health care facilities. The population of the entire suburb is included in these calculations if its centroid falls within a health service catchment. In the second step, a similar floating catchment was placed over the suburb centroid and all health care services falling in the area were identified. Accessibility was computed by summing all provider to population ratios contained within the catchment. This method has been widely used in health care access research.[40,41]

Green space data were obtained from the AURIN portal and were available for 2018 only.[42] Data included green areas such as parks, reserves, national parks, conservation areas, forest reserves, recreational areas, and other open spaces. We used the proportion of green space per suburb to assess the degree of exposure to green space. Neighborhood level obesity was operationalized as percentage of population obese (body mass index [BMI] $\geq$30 kg/m^2) in each neighborhood.[43] BMI data were extracted from Southern IML Research (SIMLR) Study database for the period 2010 to 2014. The SIMLR Study is a longitudinal, community-derived cohort comprising a near-census of data collected from individuals aged 18 years and older in Illawarra-Shoalhaven, while presenting for private pathology testing.[44] Finally, fast food data were sourced from Open Street Map,[45] company websites and the Yellow Pages,[46] and were extensively cross-checked and verified. We defined fast food outlets as service establishments that sell quickly prepared food with payment made prior to receiving food and with little table service.[47] A population-scaled measure of fast food density was derived as the number of outlets per 10 000 people, which was computed using the estimated resident populations from the 2011 Australian Census of Population and Housing.[35]

All neighborhood variables, except fast food density, were converted from their continuous form into quintiles, where Q1 represents the highest availability and Q5 the lowest. Fast food data were collapsed into a binary scale as there were many suburbs with zero outlets. The quintiles were then assigned to individual records based on their suburb of residence.

Covariates

Individual level covariates comprised age at most recent admission, gender, and country of birth. Age was categorized as 18-44, 45-65, and 65+ years. Gender was categorized as male or female. Country of birth was grouped based on the *Standard Australian Classification of Countries* produced by the Australian Bureau of Statistics.[48] The Index of Relative Socioeconomic Disadvantage (IRSD) from the 2011 Socioeconomic Indexes for Areas product[49] was included in the analysis as a neighborhood-level covariate, as previous research had reported its association with SMI-T2D comorbidity.[29] The IRSD is an aggregate measure of the socioeconomic disadvantage for areas computed on the basis of 17 variables, including education, income, occupation, unemployment, housing type, overcrowding, and English proficiency. IRSD scores were classified into quintiles in this study.

Statistical Analysis

Descriptive analysis was conducted, and variable distributions assessed. A two stage modeling approach was used, whereby a series of single exposure multilevel models were run in the first stage followed by multi-exposure models in the second stage. Separate multilevel models were run in the first stage for each of the neighborhood variables to identify the specific associations between neighborhood features and

SMI-T2D comorbidity. Three models were fit for each of the 5 neighborhood variables and T2D comorbidity in SMI, accounting for neighborhood-level clustering. The first model was unadjusted; the second adjusted for individual-level variables (age, gender, country of birth); and the third expanded model 2 with adjustment for neighborhood-level IRSD.

In the second stage, a series of multivariable random intercept logistic regression models were then calculated: first with no predictors; then with individual predictors only; and finally, with both individual- and neighborhood-level characteristics. This approach was used to estimate the intraclass correlation coefficient (ICC), and also to identify the potential confounding between various neighborhood characteristics. The ICC is the proportion of variance in the outcome variable attributed to differences between individuals in different neighborhoods as opposed to differences between individuals within the same neighborhood and was calculated by the latent variable method.[50,51] The proportion of the neighborhood-level variance explained by different neighborhood variables was also calculated.[51] The sensitivity of results to including neighborhood-level obesity was evaluated by refitting the final model excluding this variable. All neighborhood- and individual-level interactions were also examined to investigate potential cross-level effect modifications. Descriptive and multilevel analysis was completed using R (version 3.5)[52] and the statistical significance was set at $P < .05$.

Results

The study population consisted of 3816 individuals aged 18 years and older, of whom 463 (12.3%) had a SMI-T2D comorbidity (Table 1). Individuals with comorbidity were mostly females (52.9%), aged 65 years and older (38.4%), and born in Australia (73.2 %). The distributions of neighborhood variables are also given in Table 1. Variance inflation factors (VIF) were computed to ensure that multicollinearity did not bias the analysis.[53] On assessing all neighborhood variables, none showed evidence of multicollinearity (VIF <3).

Table 2 presents single-exposure (stage 1) associations between neighborhood features and SMI-T2D comorbidity. Only area level crime rates were significantly related to SMI-T2D comorbidity after adjusting for individual factors and neighborhood-level socioeconomic disadvantage (Table 2, model 3): Living in areas with a higher crime rate was associated with higher odds of SMI-T2D comorbidity compared with living neighborhoods with a lower crime rate (odds ratio [OR] 2.48, 95% CI 0.91-6.74). No significant associations were observed between health care access, neighborhood obesity, green spaces or fast food availability, and the odds of SMI-T2D comorbidity (Table 2, model 3).

When all neighborhood variables were included in multivariable models with individual-level covariates (see Table 3, model 4), area-level crime remained significantly associated with SMI-T2D comorbidity. The odds ratio for the highest crime quintile increased compared with the single exposure models and remained statistically significant (OR 2.78, 95% CI 1.02-7.57, $P = .002$). The ICC for the null model was 0.029, indicating that 2.9% of the variance in SMI-T2D comorbidity was attributable to between neighborhood differences. Addition of all the neighborhood features in model 4 (Table 3) accounted for 87.76% of between area variance and the ICC for this model was reduced to 0.004, indicating that the majority of residual variance in SMI-T2D risk was attributed to within-neighborhood rather than between-neighborhood differences. Sensitivity analysis excluding neighborhood-level obesity did not change the results substantially (Supplementary Material 1). There was no evidence of interaction between individual- and area-level variables (Supplementary Material 2).

Discussion

We examined associations between characteristics of neighborhood environments and the likelihood of SMI-T2D comorbidity. The results indicate that approximately 3% of the total variance in SMI-T2D comorbidity was attributed to neighborhood characteristics. The neighborhood variables included in this study accounted for approximately 45% of this neighborhood variation and neighborhood socioeconomic disadvantage accounted for an additional 17%. A statistically significant positive association was observed between area-level rates of crime and SMI-T2D comorbidity independent of individual-level characteristics and neighborhood-level socioeconomic disadvantage. No significant associations were observed between the other 4 neighborhood variables included: access to health care services, neighborhood-level obesity, availability of green spaces, and availability of fast food restaurants and SMI-T2D comorbidity, suggesting that it is unlikely that these neighborhood features have a large influence on SMI-T2D comorbidity.

Even though modest amounts of neighborhood variance in SMI-T2D comorbidity was reported in this study, noting that the whole population is impacted by any small changes to reduce the neighborhood disparities is important. As Geoffrey Rose has pointed out, population-based approaches have the potential to shift the risk distribution of the entire population in a favorable direction and are considered more effective in reducing the disease burden than a "high-risk" approach in which measures are targeted only to individuals with substantially higher risk.[54]

This is one of the few studies to investigate the relationship between neighborhood features and SMI-T2D

Table 1. Descriptive Characteristics of the Study Population.

Variables	Individuals with SMI (n = 3816), n (%)	Individuals with SMI + T2D (n = 463), n (%)	% comorbidity
Individual variables			
Gender			
Female	1848 (48.4)	245 (52.9)	13.3 (12.2-14.4)
Male	1968 (51.6)	218 (47.1)	11.1 (10.1-12.1)
Age, years, mean (SD)	43.6 (18.5)	58.8 (15.7)	
Age, years			
18-44	1961(51.4)	92 (19.9)	4.7 (4.0-5.4)
45-65	1213 (31.8)	193 (41.7)	15.9 (14.7-17.1)
65+	642 (16.8)	178 (38.4)	27.7 (26.3-29.1)
Country of birth			
Australia	3104 (81.3)	339 (73.2)	10.9 (9.9-11.9)
Oceania excluding Australia	74 (1.9)	12 (27.9)	16.2 (15.0-17.4)
UK and Ireland	212 (5.6)	35 (7.6)	16.5 (15.3-17.7)
Western Europe	137 (3.6)	29 (6.3)	21.2 (19.9-22.5)
Eastern and central Europe	125 (3.3)	29 (6.3)	23.2 (21.9-24.5)
Northeast Asia	17 (0.45)	0 (0.0)	0.0 (0.0-18.4)
Southeast Asia	51 (1.3)	6 (1.3)	11.8 (10.8-12.8)
Central and South Asia	16 (0.4)	3 (0.6)	18.8 (17.6-20.4)
Middle East and North Africa	39 (1.0)	9 (1.9)	23.1 (21.8-24.4)
Sub-Saharan Africa	20 (0.5)	0 (0.0)	0.0 (0.0-16.1)
Americas	21 (0.6)	1 (0.2)	4.8 (4.1-5.5)
Neighborhood variables			
IRSD scores, mean (SD)	940.5 (82.1)	934.1 (88.3)	
IRSD			
Q1 (highest disadvantage)	1752 (45.9)	229 (49.5)	13.1 (12.0-14.2)
Q2	943 (24.7)	120 (25.9)	12.7 (11.6-13.8)
Q3	620 (16.2)	75 (16.2)	12.1 (11.1-13.1)
Q4	362 (9.5)	34 (7.3)	9.4 (8.5-10.3)
Q5 (lowest disadvantage)	139 (3.6)	7 (1.5)	5.1 (4.4-5.8)
Area-level crime, mean (SD)	831.4 (615.5)	833.9 (557.2)	
Area level crime			
Q1 (highest crime)	1900 (49.8)	270 (58.3)	14.2 (13.1-15.3)
Q2	847 (22.2)	105 (22.7)	12.4 (11.4-13.5)
Q3	655 (17.2)	62 (1.6)	9.5 (8.6-10.4)
Q4	317 (8.3)	20 (0.5)	6.3 (5.5-7.1)
Q5 (lowest crime)	97 (2.5)	6 (0.2)	6.2 (5.4-7.0)
Access to health care, mean (SD)	2.2 (3.6)	2.2 (3.6)	
Access to health care			
Q1 (highest access)	833 (21.8)	114 (24.6)	13.7 (12.6-14.8)
Q2	968 (25.4)	98 (21.2)	10.1 (9.1-11.1)
Q3	1339 (35.1)	160 (34.6)	11.9 (10.9-12.9)
Q4	592 (15.5)	82 (17.7)	13.9 (12.8-15.0)
Q5 (lowest access)	84 (2.2)	9 (1.9)	10.7 (9.7-11.7)
Green space availability, mean (SD)	14.3 (18.0)	13.1 (17.5)	
Availability of green spaces			
Q1 (highest availability)	93 (2.4)	10 (2.2)	10.8 (9.8-11.8)
Q2	341 (8.9)	37 (8.0)	10.9 (9.9-11.9)
Q3	688 (18.0)	82 (17.7)	12.0 (11.0-13.3)
Q4	742 (19.4)	82 (17.7)	11.05 (10.5-12.6)
Q5 (lowest availability)	1952 (51.2)	252 (54.4)	12.9 (11.1-13.1)

(continued)

Table 1. (continued)

Variables	Individuals with SMI (n = 3816), n (%)	Individuals with SMI + T2D (n = 463), n (%)	% comorbidity
Neighborhood obesity, mean (SD)	17.9 (3.8)	18.0 (3.8)	
Neighborhood obesity			
Q1 (highest obesity)	1444 (37.8)	175 (37.8)	12.1 (11.1-13.1)
Q2	974 (25.5)	118 (25.5)	12.1 (11.1-13.1)
Q3	873 (24.0)	100 (22.4)	11.5 (10.4-12.5)
Q4	446 (10.6)	64 (13.0)	14.3 (13.2-15.4)
Q5 (lowest obesity)	79 (2.1)	6 (1.3)	7.6 (6.8-8.4)
Fast food availability, mean (SD)	9.3 (8.1)	10.0 (9.8)	
Fast food availability			
Available (>0)	3157 (82.7)	380 (82.1)	12.0 (10.8-13.0)
Not available (0)	659 (17.3)	83 (17.9)	12.6 (11.6-13.7)

Abbreviation: ISRD, Index of Relative Socioeconomic Disadvantage.

comorbidity. To the best of our knowledge, this is also the first report of a direct association between objectively measured area-level crime and T2D risk in individuals with SMI. Our results parallel those of a recent study from the United States, which reported an increased odds of depression and T2D comorbidity in neighborhoods with higher perceived neighborhood problems such as violence.[55] Other research has also connected perceived neighborhood crime rate to independent T2D incidence[32,56] as well as to the risk factors of T2D such as psychological distress, lower physical activity, and obesity.[18,19,57,58] Furthermore, persistent exposure to fear and stress are proposed to alter immune system response and activate the hypothalamic pituitary adrenal axis accelerating the development of T2D.[1,59]

In contrast to previous studies on independent T2D risk, we identified no significant association between SMI-T2D comorbidity and neighborhood resources such as health care access, fast food availability, and green spaces. However, one previous study by Kirkpatrick et al[60] had reported increased T2D risk in psychosis patients independent of access to care. One potential explanation for these null findings could be that individuals with SMI may have trouble changing an unhealthy lifestyle despite the availability of resources due to their psychosocial disability and cognitive impairment.[61,62] For example, lower physical activity could be due to negative symptoms and social isolation, and neighborhood level green space may not be a relevant resource for physical activity in individuals with SMI. Similarly, negative and psychotic symptoms can be barriers to accessing health care services despite availability.[4,60] The null results may also be attributable to differences in study design, neighborhood measures assessed, the way in which constructs were evaluated (eg, density vs distance, quantity vs quality), and the population examined. With regard to health care access, it should be noted that Australia has a national health care scheme (Medicare), envisioned to deliver the most equitable and efficient health care access at reduced or no cost.[63] This along with several Australian Government initiatives to improve health care access for people with mental illness may have resulted in decreased inequities in health care access for this population. It is unlikely for an effect to be detected without variations in neighborhood exposures. The lack of association of SMI-T2D comorbidity with health care access may also be due to the inefficiency of current primary care interventions designed for general population in reaching disadvantaged groups such as individuals with SMI, as suggested by a systematic review by Glazier et al.[64] Hence individuals with SMI may require additional support to utilize the available resources to achieve the same effect realized by individuals without SMI. Further research is needed to draw definitive conclusions.

Strengths and Limitations

Strengths of our study include a large sample of clinically coded individuals with SMI, assessment of multiple environment features, use of objectively measured neighborhood data collected from different sources, and multilevel analysis. Limitations include the cross-sectional design, which prevents us from drawing causal inferences. Individual-level data used in this study were sourced only from inpatient mental health records and did not consider outpatient and private practice records. The Australian National Surveys of Psychosis indicates that 45.6% to 62.9% of people with SMI reported ≥1 hospital admission for any reason in the previous 12 months.[65] As such, our 8-year data collection period should have provided a reasonable coverage of the study population. It is also possible that our results are influenced by temporal misalignment as neighborhood-level data were collected for different time periods due to the nonavailability of historical data on these

Table 2. Results of Single Exposure Multilevel Logistic Regression.[a]

	Model 1		Model 2		Model 3	
Variable	Odds ratio (95% CI)	*P*	Odds ratio (95% CI)	*P*	Odds ratio (95% CI)	*P*
Area-level crime	1.17 (0.97-1.41)	.002	1.19 (0.99-1.44)	.013	1.02 (0.82-1.28)	.032
Area-level crime						
Q1 (highest crime)	2.90 (1.21-6.97)		3.08 (1.28-7.44)		2.48 (0.91-6.74)	
Q2	2.30 (0.94-5.60)		2.59 (1.06-6.35)		2.11 (0.77-5.76)	
Q3	1.59 (0.65-3.94)	<.001	1.61 (0.65-3.99)	<.001	1.27 (0.46-3.49)	.001
Q4	1.00 (0.37-2.66)		1.17 (0.43-3.13)		1.02 (0.36-2.83)	
Q5 (lowest crime)	1.00		1.00		1.00	
Access to health care	1.0 (0.89-1.12)	.984	0.99 (0.88-1.11)	.87	1.05 (0.94-1.19)	.385
Access to health care						
Q1 (highest access)	1.34 (0.61-2.94)		1.46 (0.66-3.21)		1.68 (0.76-3.71)	
Q2	0.96 (0.43-2.11)		1.05 (0.47-2.33)	.386	1.11 (0.47-2.33)	.241
Q3	1.18 (0.54-2.57)		1.27 (0.58-2.78)		1.35 (0.62-2.96)	
Q4	1.39 (0.62-3.09)		1.42 (0.63-3.16)		1.39 (0.63-3.09)	
Q5 (lowest access)	1.00		1.00		1.00	
Availability of green spaces	0.91 (0.81-1.03)	.137	0.90 (0.79-1.00)	.064	0.94 (0.83-1.08)	.378
Availability of green spaces						
Q1 (highest availability)	0.74 (0.36-1.52)		0.72 (0.34-1.50)		1.08 (0.50-2.32)	
Q2	0.76 (0.50-1.18)		0.73 (0.47-1.12)		0.88 (0.56-1.37)	
Q3	0.82 (0.58-1.16)	.318	0.81 (0.58-1.14)	.285	1.02 (0.70-1.47)	.511
Q4	0.71 (0.50-1.02)		0.73 (0.52-1.02)		0.76 (0.54-1.07)	
Q5 (lowest availability)	1.00		1.00		1.00	
Neighborhood obesity	1.05 (0.93-1.19)	.39	1.05 (0.93-1.19)	.426	1.00 (0.99-1.00)	.384
Neighborhood obesity						
Q1 (highest obesity)	1.85 (0.76-4.53)		1.65 (0.66-4.10)		1.19 (0.48-2.97)	
Q2	1.66 (0.67-4.10)		1.53 (0.61-3.83)		1.39 (0.56-3.49)	
Q3	1.60 (0.64-3.99)	.481	1.47 (0.59-3.70)	.532	1.54 (0.60-3.96)	.157
Q4	2.05 (0.81-5.17)		1.95 (0.75-4.99)		2.03 (0.79-5.26)	
Q5 (lowest obesity)	1.00		1.00		1.00	
Fast food availability	1.08 (0.98-1.20)	.129	1.07 (0.96-1.19)	.215	1.03 (0.92-1.16)	.544
Fast food availability						
Not available (0)	1.01 (0.75-1.36)	.927	1.08 (0.80-1.44)	.617	1.29 (0.91-1.75)	.107
Available (>0)	1.00		1.00		1.00	

[a]Model 1: Unadjusted. Model 2: Adjusted for individual-level variables. Model 3: Adjusted for individual-level variables and neighborhood Index of Relative Socioeconomic Disadvantage. Odds ratios for continuous variables expressed as odds per standard deviation.

Table 3. Multivariable Regression Analysis.[a]

Variables	Model 1 Odds ratio	Model 1 P	Model 2 Odds ratio	Model 2 P	Model 3 Odds ratio	Model 3 P	Model 4 Odds ratio	Model 4 P
Individual variables								
Sex								
Female			1.00		1.00		1.00	
Male			0.95 (0.78-1.17)	.658	0.96 (0.78-1.17)	.687	0.96 (0.78-1.18)	.685
Age (years)								
18-44			1.00		1.00		1.00	
45-65			3.79 (2.91-4.93)		3.78 (2.90-4.92)		3.77 (2.88-4.92)	
65+			7.68 (5.77-10.23)	<.001	7.82 (5.87-10.42)	<.001	7.87 (5.89-10.51)	<.001
Country of birth								
Australia			1.00		1.00		1.00	
Oceania excluding Australia			1.57 (0.81-3.03)		1.53 (0.79-2.97)		1.57 (0.81-3.04)	
UK and Ireland			0.84 (0.57-1.26)		0.88 (0.59-1.31)		0.85 (0.57 -1.26)	
Western Europe			0.99 (0.63-1.54)		0.97 (0.62-1.52)		0.99 (0.63 -1.55)	
Eastern and central Europe			1.30 (0.82-2.05)		1.30 (0.82-2.06)		1.38 (0.87-2.19)	
Southeast Asia			1.30 (0.53-3.19)		1.30 (0.52-3.19)		1.25 (0.51-3.07)	
Central and South Asia			2.03 (0.53-7.82)		2.13 (0.56-8.10)		2.09 (0.55-7.98)	
Middle East and North Africa			1.84 (0.83-4.09)		1.87 (0.84-4.16)		1.94 (0.87-4.32)	
Americas			0.42 (0.06-3.25)	.137	0.41 (0.05-3.15)	.149	0.39 (0.05-3.04)	.145
Neighborhood variables								
IRSD quintiles								
Q5 (least disadvantaged)					1.00		1.00	
Q4					1.87 (0.77-4.53)		1.57 (0.59 -4.19)	
Q3					2.67 (1.14-6.15)		1.73 (0.65-4.67)	
Q2					2.92 (1.28-6.67)		1.97 (0.72-5.35)	
Q1 (most disadvantaged)					3.20 (1.42-7.20)	0.008	1.96 (0.69-5.51)	.69
Area-level crime								
Q5 (lowest crime)								
Q4							1.00	
Q3							0.97 (0.34-2.73)	
Q2							1.56 (0.57-4.27)	
Q1 (highest crime)							2.20 (0.81-5.99)	
							2.78 (1.02-7.57)	0.001
Variance of random effects								
T^2	0.098		0.073		0.056		0.012	
PCV	Reference		25.50%		42.90%		87.76%	
ICC	0.029		0.0217		0.017		0.004	

Abbreviations: IRSD, Index of Relative Socioeconomic Disadvantage; PCV, Proportion Change in Variance; ICC, Intraclass Correlation Coefficient; T^2, Area level variance

[a]Only significant neighborhood variables reported. Model 1: Null model with suburban-level random effect. Model 2: Model 1 + individual-level factors. Model 3: Model 2 + neighborhood-level IRSD quintiles. Model 4: Model 3 + neighborhood variables.

neighborhood variables. Individual socioeconomic status, which is often used in neighborhood studies, was also not available for inclusion in this analysis. Likewise, information regarding the level of diabetes and SMI control was not available for inclusion in this study. In addition, multilevel modeling approach employed in this study may be limited in its ability to provide optimal information on the spatial distribution of outcomes, as it fragments space into arbitrary administrative areas and ignores the spatial association between them.[66] However, Moran's *I* statistics of area-level residuals did not reveal spatial autocorrelation unaccounted by multilevel models used in this study,[67] indicating further spatial exploration is unwarranted. We also acknowledge the limitation of using neighborhood obesity as a proxy for neighborhood cues for obesogenic environment. However, sensitivity analysis excluding the variable did not alter the results substantially.

Conclusions

T2D comorbidity in SMI is a major public health issue. While many studies investigating this association looked at the individual level factors, we examined the added influence of neighborhood contextual environments on SMI-T2D comorbidity. We observed that individuals with SMI residing in areas with higher crime rates were more likely to report T2D comorbidity compared to individuals with SMI residing in lower crime rate areas, even after controlling for individual-level variables and neighborhood-level disadvantage. The study provides a case for primary and community health stakeholders to be mindful of the neighborhood discrepancies in SMI-T2D comorbidity. The findings support targeted neighborhood level initiatives aimed at individuals with SMI living in high-crime neighborhoods in order to reduce the public health burden imposed by SMI-T2D comorbidity. Overall, the study suggests that the mechanisms of neighborhood influence on SMI-T2D are highly complex. Further research is needed incorporating longitudinal study designs, data from different geographic locations, more rigorous measurements, variables not included in this study and mediation analysis to further understand the mechanisms linking neighborhoods and T2D comorbidity in SMI, with the aim of informing policies and practices that may reduce the burden.

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Author Contributions

RW undertook literature review, contributed to the research design, analysed and interpreted the data and drafted the manuscript. AB, XF, DM and NP supervised the project, contributed to the study design, helped with the interpretation of results, critically reviewed the manuscript and helped draft the final version for submission.

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Supplemental Material

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