Physical inactivity displays a mediator role in the association of diabetes and poverty: A spatiotemporal analysis

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Abstract

Physical inactivity is one of the risk factors of diabetes. In addition, physical inactivity is attributed to urbanization-related factors, such as poverty, which is also one of the risk factors of diabetes. We hypothesized that physical inactivity is a mediator in the association between diabetes and poverty, and that spatial heterogeneity exists in these relationships. This study adopted a spatiotemporal modelling approach to conduct this mediator analysis. From 2004-2011, data were collected at the county level in 48 contiguous states (with a total of 3,109 counties) from the Behavioral Risk Factor Surveillance System (BRFSS) and American Community Survey. Poverty percentage significantly affected physical inactivity prevalence and diabetes prevalence in two separate models. Using a model with both physical inactivity and poverty percentages as independent variables, we verified that physical inactivity prevalence is a significant mediator. In this model, physical inactivity prevalence resulted in a significant positive association with diabetes prevalence, and the influence of poverty percentage on diabetes prevalence was significantly reduced (P=0.0009). An advanced spatiotemporal analysis revealed that 32.65% of counties having a significant positive association between diabetes prevalence and physical inactivity prevalence also had a significant positive association between physical inactivity prevalence and poverty percentage. Those counties were also likely located in the South and Southeast of USA. In summary, the findings of this study demonstrate the mediating effect of physical inactivity between diabetes and poverty. When implementing diabetes prevention in communities with higher poverty, appropriate strategies to reduce the cost burden of physical activity programmes should be considered.

Introduction

Diabetes prevalence has consistently increased in recent years, and physical inactivity has proven to be a significant risk factor for this disease. Physical inactivity should be seen as a health misbehaviour, which can seriously affect human health. According to a World Health Organization (WHO) report, insufficient physical activity is a key risk factor for non-communicable diseases, including diabetes (WHO, 2015a). More than 23% of the world's adults (aged 18 and over) do not have a sufficient level of physical activity. The discouragement of physical activity participation can be attributed to several environmental factors, like high crime rate, high-density traffic, low air quality and the lack of sports facilities

(WHO, 2015b). These urbanisation-related factors may stem from poverty, which has been named a leading cause of Type 2 diabetes. Risk factors for diabetes include both poverty and physical inactivity. Physical inactivity is a significant risk factor for diabetes (Booth and Hawley, 2015). In addition, lack of physical activity has become a global problem associated with diabetes (Oggioni *et al*., 2014). Promoting physical activity is usually regarded as the primary prevention of diabetes (Avery *et al*., 2012); however, there are challenges because physical inactivity has a complicated relationship with other health behaviours and policy and environmental change (Kohl *et al*., 2012). Furthermore, disparities of physical activity by sociodemographic characteristics also exist in the USA (Ham and Ainsworth, 2009).

Additionally, the association between physical inactivity and poverty has been demonstrated (Riste *et al*., 2001). Results from a study conducted in a city in southern California indicated that residents in high poverty areas had less exercise. Instead, they spent more time watching electronic media as compared to those from low poverty neighbourhoods (Cohen *et al*., 2012). High poverty neighbourhoods were also less pleasurable for outdoor physical activity because the areas were less safe and the sidewalks and streets not maintained well (Franzini *et al*., 2010). Another study found the prevalence of leisure time inactivity was highest among study participants from the lower social classes (Marshall *et al*., 2007). In USA, physical inactivity dropped from 42.6% among study participants from the lowest income category to 15.1% among study participants from the highest income category (Pratt *et al*., 1999).

In USA, diabetes has found to show spatial variation in incidence and prevalence at the county-level. For example, in Medicaid recipient adults in South Carolina, living in a county with high levels of poverty was positively associated with diabetes prevalence (Stewart *et al*., 2011). A spatial analysis study showed that physical inactivity prevalence has a significant inverse relationship with diabetes prevalence in north-western USA, and a significant positive relationship between poverty percentage and diabetes prevalence was more likely observed in the Southwest and Northeast of the country (Hipp and Chalise, 2015). The positive association between poverty and diabetes is normally analysed using a linear model; however, after taking geographical location into account, the diabetes-poverty association can fluctuate spatially. For example, a spatial analysis applied a geographic weighted regression model to explore the macro-level spatial non-stationary of the diabetes-poverty relationship, and this study provided evidence that poverty may not always be positively associated with diabetes, especially in the states of Texas, Kansas and Washington (Siordia *et al*., 2012). Hence, it is plausible that geographic heterogeneity may exist, but further investigation is needed to determine the association between diabetes and poverty.

Certain variables may mediate the association between diabetes and the other risk factors. For instance, psychosocial factors, unhealthy behaviours and obesity may mediate the association between socioeconomic status and diabetes incidence (Demakakos *et al*., 2012). Usual source of care may also mediate the association between health insurance and diabetes (Hastings and Hawkins, 2009). Since studies have shown physical inactivity is a risk factor of diabetes, and poverty is a risk factor of both diabetes and physical inactivity, we hypothesized whether physical inactivity is actually a mediator in the association between poverty and diabetes rather than a purely risk factor of diabetes. This relationship has not yet been fully investigated.

This study retrospectively collected prevalence and poverty data in USA at the county level from a nationwide survey database and aimed to investigate whether physical inactivity mediates the association between diabetes and poverty. We applied an advanced spatiotemporal analysis to consider spatial variation and geographic heterogeneity among our data. Additionally, we aimed to identify physical inactivity as a significant modifier in counties vulnerable to diabetes and poverty. By using geographic information visualization, this study distinguished spatial clusters in the study areas.

Materials and Methods

Study area

We used county as the geographic unit in this research because it is the smallest geographic data collected by the Behavioral Risk Factor Surveillance System (BRFSS). A total of 3,109 counties in the 48 contiguous states in USA were included in the study area, and each county had at least one adjacent county, which was defined by sharing any part of a boundary with another county.

Data sources

From 2004-2011, age-race-gender adjusted diabetes prevalence and physical inactivity prevalence were gathered at the county level from official website of the U.S. Centers for Disease Control and Prevention (https://www.cdc.gov/diabetes/data/county.html). We also used adjusted obesity prevalence for the sensitivity analysis. Poverty percentage and other important socioeconomic predictors were selected from the database of American Community Survey (ACS) maintained by the U.S. Census Bureau since 2005. Currently, this decennial survey provides the most detailed information related to population distribution, social structure, economic condition, and housing status for each county (US Census Bureau, 2014). Every year the U.S. Census Bureau publishes 1-year, 3-year and 5-year ACS data. This study used 5-year ACS estimates to guarantee complete data. Two 5-year estimates were adopted, while the first 5-year estimate (2005-2009) was applied to the data before 2009, and the second (2008-2012) was applied to the data after 2009. All ACS data can be downloaded from American Fact Finder (https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml).

Variables

The diabetes prevalence were calculated from respondents who were diagnosed with diabetes. A respondent was considered diabetic if he/she answered *yes* to the question: *Has a doctor, nurse, or other health professional ever told you that you have diabetes?* Note that females who had gestational diabetes were not included in the calculation of diabetes prevalence. The physical inactivity prevalence was calculated using respondents who reported doing no physical activity or exercise in the past 30 days. These respondents were identified as those who answered *no* to the question: *During the past month, other than your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?* Those county-level prevalence data were estimated by applying Bayesian multilevel modelling techniques on individual data from the largest nationwide telephone survey - the BRFSS (CDC, 2016). Poverty

percentage data was calculated using the percentage of families and people whose income during the past 12 months was below the poverty level. We selected several confounding variables, which included gender (male percentage), age (elder percentage and median age), race (Hispanic percentage, non-Hispanic White percentage and non-Hispanic Black percentage), percentage of at least high school education, health insurance coverage percentage and occupation percentages (management/business/science/art, service, sales/office, natural resources/construction/maintenance and production/transportation/material moving). Smoking prevalence was also considered a confounding variable. Smoking prevalence was calculated as the prevalence of current total cigarette smoking in nondaily and daily current smokers, which were determined by the two questions in the BRFSS: *Have you smoked at least 100 cigarettes in your entire life* and *Do you now smoke cigarettes every day, some days or not at all?*, respectively. The smoking prevalence data at the county level were estimated by the small area estimation approach, and they were published for public-use (Dwyer-Lindgren *et al.*, 2014). Finally, for sensitivity analysis, we included obesity prevalence, which was identified from the same data source as diabetes and physical inactivity, and respondents were considered obese if their body mass index was 30 or greater (CDC, 2016).

Statistical analysis

In order to test whether physical inactivity is a mediator in the association between diabetes and poverty among counties, the following three models were built:

Model I: $DM = \alpha_1 + \beta_1 \times POV + \gamma_1 \times X + f(time) + f_{spat}(c)$

Model II: $PHY = \alpha_2 + \beta_2 \times POV + \gamma_2 \times X + f(time) + f_{spat}(c)$

Model III: $DM = \alpha_3 + \beta_{31} \times PHY + \beta_{32} \times POV + \gamma_3 \times X + f(time) + f_{spat}(c)$

where variables DM, PHY and POV are adjusted diabetes prevalence, adjusted physical inactivity prevalence and poverty percentage at the county level, respectively. All 14 confounding variables were denoted by a vector X. Fixed intercepts and slopes were denoted by (α_1, α_2, α_3) and (β_1, β_2, β_{31}, β_{32}, γ_1, γ_2, γ_3), which were estimated by the structured additive regression (STAR) modelling approach with a fully Bayesian method using a Markov chain Monte Carlo simulation technique (Brezger and Lang, 2006). Variances of unknown smoothing parameters were estimated with priors in terms of an inverse Gamma distribution with two hyperparameters (a, b)=(0.001, 0.001) by default. Each model took temporal autoregressive correlation and spatial autocorrelation (*i.e.* the correlation of a variable with itself through space) into account by adding f(time) with a B-spline function for calendar time and $f_{spat}(c)$ with a spatial function for locations c. In particular, the spatial function was the Markov random fields (Kindermann and Snell, 1980) to analyse boundary data and to emphasize the relationship of adjacent areas. In detail, we defined a neighbourhood as an adjacent county c' sharing the same boundaries of another county c. Each county had a neighbourhood set Ω_c with a total number of neighbourhoods $N_c \geq 1$, which means that each county should have at least one neighbourhood. The Markov random fields follow a normal distribution with mean $\sum_{c' \in \Omega_c} f_{spat}(c')/N_c$

and variance σ_c^2/N_c, where $f_{spat}(C')$ is the spatial effect of an adja-

cent county c', and σ_c^2 the original variance of county c. We interpreted the coefficient β_{32} as the direct effect, and the product of β_1 and β_{32} as the indirect effect of a unit increase in poverty prevalence with respect to the mediator (*i.e.*, physical inactivity prevalence). The identified criterion of regarding physical inactivity as a mediator relies on the four linear estimates (β_1, β_2, β_{31}, β_{32}), where β_1, β_2, and β_{31} are statistically significant, and β_{32} is smaller in absolute value than β_1. The significance of βs was determined by the 95% credible interval (CI) of an estimate strictly greater than 0. We eventually applied the Sobel test to compute a P value to identify the significance of the mediating effect (Sobel, 1982; Baron and Kenny, 1986).

For the purpose of investigating spatial clusters of significant association between diabetes and physical inactivity caused by poverty, an advanced spatiotemporal analysis was carried out by applying the following two models:

Model IV: $DM = \alpha_4 + PHY \times f_{spat}(c) + \gamma_4 \times X + f(time)$

Model V: $PHY = \alpha_5 + POV \times f_{spat}(c) + \gamma_5 \times X + f(time)$

where physical inactivity prevalence and poverty percentage were no longer linear terms but interacted with a spatial function to represent county-specific influence on dependent variables. The two interaction terms are equivalent to spatially weighted county-specific random slopes for physical inactivity and poverty percentage. Counties having a 95% CI of spatial estimate strictly greater than 0 in the spatial function $f_{spat}(c)$ in Model IV and Model V were regarded as clustering areas vulnerable to diabetes caused by physical inactivity, which can be attributed to a high-poverty percentage. We also accomplished a model diagnostic in autocorrelation and sampling path. Finally, a sensitivity analysis was conducted to test whether our findings were robust by choosing different hyperparameters.

Data management was done by SAS v9.3 (SAS Institute Inc., Cary, NC, USA). Spatiotemporal analysis was accomplished by BayesX v3.0.2 (Brezger *et al.*, 2005). Results of spatial functions were visualized on maps by using ArcGIS v10 (ESRI Inc., Redlands, CA, USA).

Results

On average, each county had 5.64 adjacent counties [standard deviation (SD)=1.36], and Washoe County in Nevada had the most adjacent counties (n=13). Figure 1 shows a clear pattern of the geographic distribution of the average adjusted diabetes prevalence, which ranged from 3.90% to 16.03%. No county had an average of adjusted physical inactivity prevalence less than 10%. Higher averages of adjusted diabetes prevalence were more likely clustered in the southeastern counties, where there were also higher averages of adjusted physical inactivity prevalence. The maximum average of poverty percentage was 43.70%, and a few high poverty clusters were found in southeastern and southern USA.

The mediator analysis shows that physical inactivity prevalence might be a mediator to diabetes prevalence. In Model I, the poverty percentage was significantly associated with diabetes prevalence. For each 1% increase of poverty percentage, there was a 0.013% (95% CI=0.008, 0.020) increase in diabetes prevalence.

In Model II, the poverty percentage was also significantly related to physical inactivity prevalence. For each 1% increase in poverty percentage, there was a 0.039% (95% CI=0.018, 0.060) increase in physical inactivity prevalence. In Model III, the prevalence of physical inactivity still had a significant impact on diabetes prevalence (estimated coefficient=0.018; 95% CI=0.014, 0.022), while the estimated coefficient of poverty percentage reduced to 0.012 (95% CI=0.006, 0.018) from the original estimate in Model I. The Sobel test verified a significant mediating effect (P=0.0009) in terms of physical inactivity prevalence.

The advanced spatiotemporal analysis from Model IV demonstrates a significant spatial variation of diabetes prevalence caused by physical inactivity prevalence. Table 1 shows that 62.11% (1,931/3,109) of the counties had a significant increase in diabetes prevalence when physical inactivity prevalence increased. Harris County, Georgia had the greatest increase in diabetes prevalence as every 1% increase in physical inactivity prevalence elevated diabetes prevalence by 0.109% (95% CI=0.094, 0.125). The geographic pattern shown in Figure 2A demonstrates that three-fifths of counties had high diabetes prevalence caused by high physical inactivity prevalence, especially in counties located in the Southeast and Northeast of the country. Table 1 also reveals that 39.56% (1,230/3,109) of the counties had a significant positive

association between physical inactivity prevalence and poverty percentage. The greatest impact of poverty on physical inactivity was found in Fairfox City, Virginia (estimated coefficient=0.937; 95% CI=0.596, 1.282). Figure 2B demonstrates the counties with a significant increase in physical inactivity prevalence caused by high poverty percentage were mostly located in southern, southeastern, and mid-northern USA. There is a large overlap in significantly spatial positive between Figure 2A and B. A total of 1,015 counties (32.65%) were significantly vulnerable to diabetes due to physical inactivity as well as vulnerable to physical inactivity due to poverty. Figure 2C shows that most of those overlapping high-risk counties were located in the south and southeast USA. The significance of the two spatial functions in the two models was moderately correlated (Spearman's correlation=0.39).

Model diagnostics in Figure 3 presents that the autocorrelations along with all lags were within ±0.1, which suggests a good control of autocorrelation in our models. In addition, the sampling path plots verified a stable trace over iterations for main predictors. In the sensitivity analysis, the linear coefficients of physical inactivity prevalence and poverty percentage in Model I, II & III were robust (Table 2). We also confirm that different hyper-parameters did not affect our main findings in the spatial functions; shown in Figure 4.
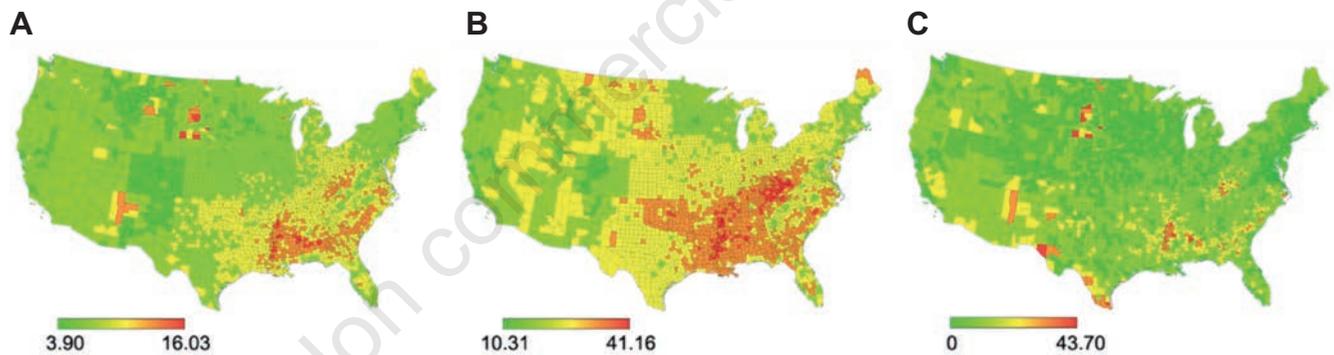
Figure 1. Average adjusted diabetes prevalence (A), average adjusted physical inactivity prevalence (B), and average poverty percentage in the USA (C).

Table 1. Summary statistics of spatial estimates in terms of the results of significance derived in Models IV and V.

	N	%	Spatial estimate				
			Min	Q1	Median	Q3	Max
Model IV							
Significant positive	1931	62.11	0.011	0.029	0.042	0.056	0.109
Significant negative	512	16.47	-0.071	-0.042	-0.030	-0.022	-0.012
Non-significance	666	21.42	-0.022	-0.006	0.003	0.009	0.020
Model V							
Significant positive	1230	39.56	0.047	0.153	0.223	0.316	0.937
Significant negative	738	23.74	-1.110	-0.515	-0.325	-0.199	-0.053
Non-significance	1141	36.7	-0.266	-0.044	0.014	0.062	0.303

Discussion

Unlike diabetes risk factors, such as gender, family history and ethnicity, which cannot be changed, the risk factor of insufficient physical activity can be reversed. Other factors may contribute to a decrease in physical activity. This study hypothesised that pover-ty may be a plausible reason that people are not able to participate in physical activity. By collecting governmental data to compose large scale measurements of diabetes, physical inactivity, and poverty, this study found the following results: i) Physical inactivity is a significant mediator in the association between diabetes and poverty; ii) People living in south-eastern and north-eastern USA
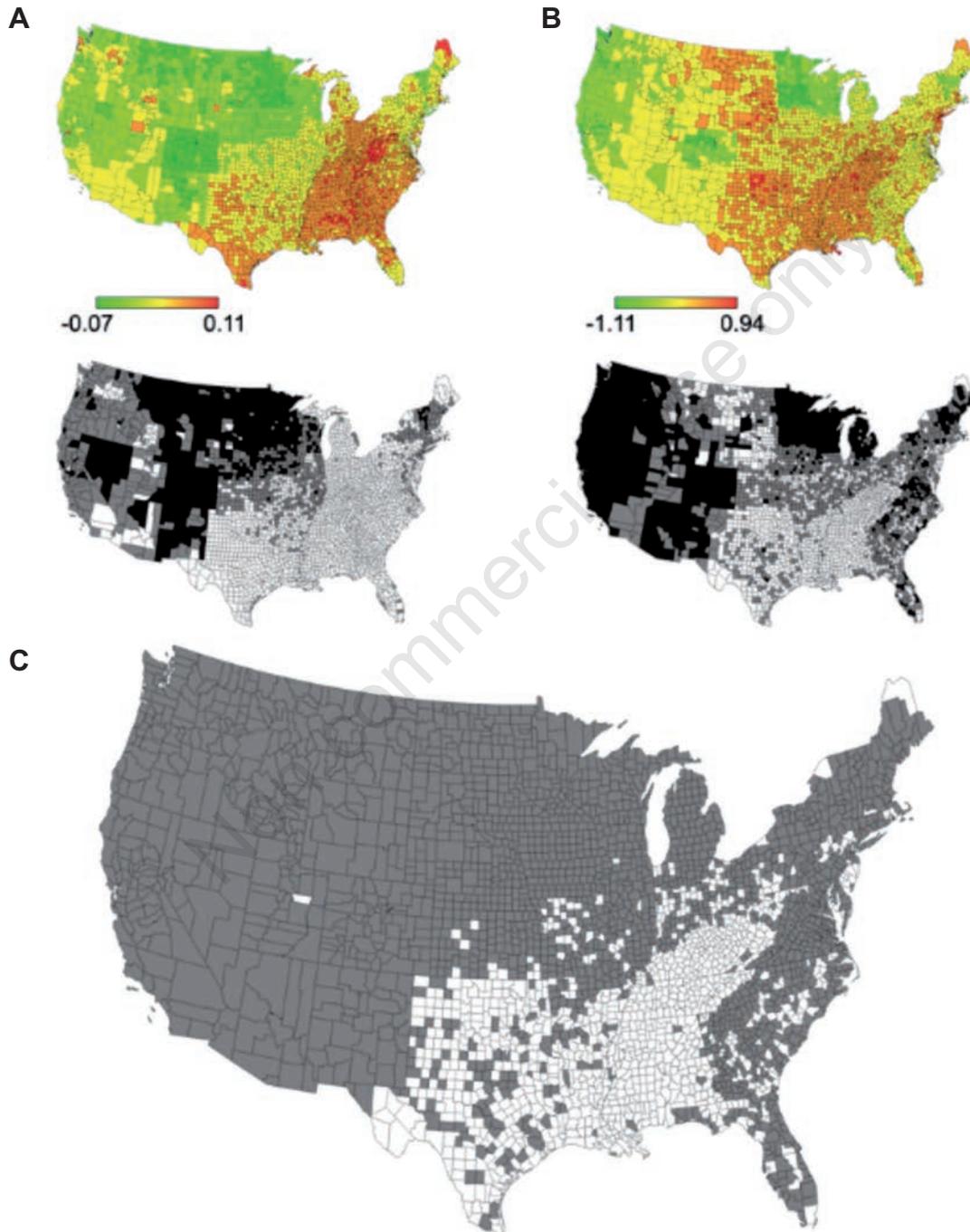
Figure 2. Geographic distribution of spatial interacted estimates. A) Physical inactivity prevalence in upper plot with spatial significance maps (white=significant positive; black=significant negative; grey=non-significance) in lower plot. B) Poverty in upper plot with spatial significance maps (white=significant positive; black=significant negative; grey=non-significance) in lower plot. C) White areas show counties with significant positive findings in both significance maps in (A) and (B).
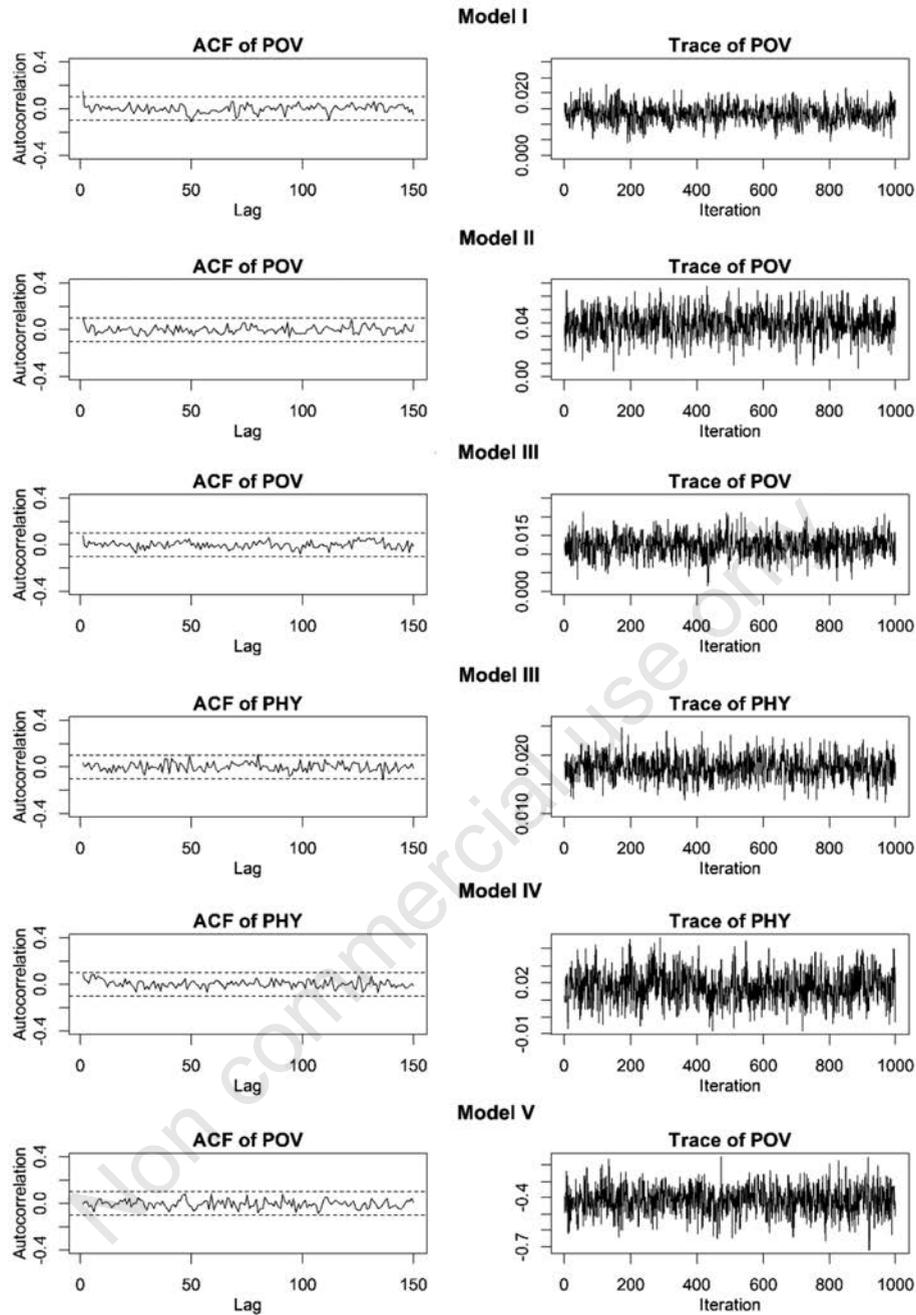
Figure 3. Autocorrelation function and sampling path for main predictors in Models I to V.

Table 2. Sensitivity analysis for Models I, II and III by using different hyper-parameters in poverty percentage and physical inactivity prevalence. By default, we used hyper-parameters a=0.001 and b=0.001.

	(a, b)=(0.001, 0.001) Estimate (95% CI)	(a, b)=(0.00001, 0.00001) Estimate (95% CI)	(a, b)=(1, 0.05) Estimate (95% CI)
Model I			
POV	0.013 (0.008, 0.020)	0.013 (0.007, 0.018)	0.013 (0.007, 0.019)
Model II			
POV	0.039 (0.018, 0.060)	0.039 (0.019, 0.059)	0.039 (0.018, 0.059)
Model III			
POV	0.012 (0.006, 0.018)	0.012 (0.007, 0.018)	0.012 (0.007, 0.018)
PHY	0.018 (0.014, 0.022)	0.018 (0.014, 0.022)	0.018 (0.014, 0.022)

CI, confidence interval; POV, poverty; PHY, physical (inactivity).

are most likely to have developed diabetes due to physical inactivity; iii) Almost two-fifths of all counties in USA had significantly higher physical inactivity prevalence due to high poverty percentage; iv) A large proportion of counties in most south or south-eastern states had significant associations with diabetes, physical inactivity and poverty. By using data with multiple years, our findings showed many counties to be at high risk for diabetes due to physical inactivity in USA. Within 15 southern states consisting of 644 counties, there is a concentrated area of high diabetes prevalence known as the *diabetes belt*. One study reported counties not located in the diabetes belt had a higher correlation between physical activity and diabetes (Barker *et al.*, 2011). This conflicting evidence is possibly caused by the statistical analysis being applied in diabetes belt and non-diabetes belt counties separately. In 2007, an advanced investigation applied a spatial cluster analysis to divide USA counties into five clusters in terms of age-adjusted diabetes prevalence (Shrestha *et al.*, 2012). This study showed that physical inactivity may also significantly impact some counties out of the diabetes belt. We explored the spatial association of diabetes prevalence, in terms of poverty percentage and physical inactivity percentage, and we identified more high-risk counties than the 644 included in diabetes belt.

Applying a spatial model in our study shows the geographic variation of influential areas. Even though this application is rarely used in diabetes and poverty research, we found a few previous studies adopting spatial methods or geographic information tools. For example, a study used a geographically weighted regression to explore the diabetes-poverty macro-level statistical relationship at the county level in USA (Siordia *et al.*, 2012). The geographical association between poverty prevalence and diabetes prevalence was significant even though physical inactivity was not included in the study. Additionally, a study in 82 Mississippi counties adopted a spatial lag model to investigate disparities of a low-density lipoprotein cholesterol test, resulting in a negative association with poverty among the elderly with diabetes (Sharma, 2014). In recent years, using geographic information systems has been suggested to target diabetes-related public health efforts. A study with 83 counties in Michigan developed study maps to highlight areas with higher diabetes and poverty rates for interventions targeting low-income minority populations with diabetes, and then used

advanced statistical analysis to verify the significance (Curtis *et al.*, 2013). The STAR model has been applied in a diabetes study previously (Chien *et al.*, 2015), while this is the first time to have it in a mediator analysis. The advanced spatial analysis used in Model IV & V showed almost one-third counties were vulnerable to diabetes because of physical inactivity and also were vulnerable to physical inactivity because of poverty. More research is needed to establish a new research strategy for investigating whether physical inactivity displays a mediator role in the association between diabetes and poverty in those counties.

Traditional diabetes research usually uses both poverty and physical inactivity as confounding variables (Jiang and Pearlman, 2013; Adeniyi *et al.*, 2015; Grundmann *et al.*, 2014). While poverty is a proven risk factor for physical inactivity, this study applied a mediator analysis to evaluate the direct effect between poverty and diabetes prevalence from the parameter of poverty (*i.e.*, β_{32}) in Model III, and we found that an indirect (mediated) effect also existed from the two parameters of poverty (*i.e.*, β_1 and β_2) in Model I & II. Note that the mediated effect should be explained conservatively because it was conducted from population data. Future research should investigate the mediated effect of physical inactivity between poverty and diabetes using individual data.

Our study regarded poverty as a predictor of both diabetes and physical inactivity, and physical inactivity was identified as a modifier in this relationship. Health interventions should consider strategies to reduce financial burden when promoting physical activity programs for diabetes prevention, especially in low-income communities. Poverty is associated with adverse health behaviours and insufficient medical treatment (Do and Finch, 2008). However, solving individual or household-level financial problems in a short time is usually difficult; therefore, managing health care for people living in poverty becomes a difficult task. For example, without enough stimulations or incentives, people living in poverty may not be willing or have time to participate in physical activity programs as they may have to spend their time trying to earn money to pay for living expenses (Borodulin *et al.*, 2015). Poverty is also an obstacle of retrieving health-related information. People living in poverty may have less access to resources that encourage physical activity. Therefore, when establishing diabetes and physical activity interventions, providing access to facil-
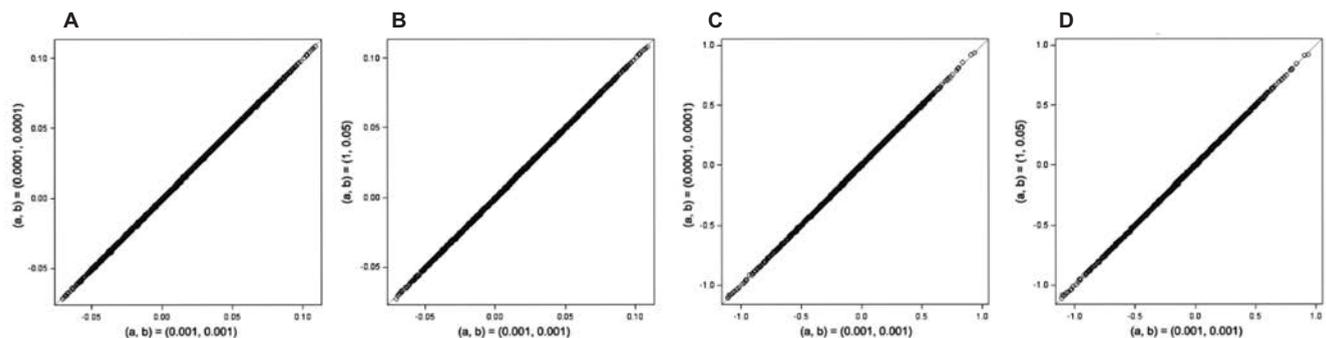

Figure 4. Sensitivity analysis for Model IV (A and B) and Model V (C and D) by using different hyper-parameters in spatial functions. By default, we used hyper-parameters a=0.001 and b=0.001.

ities, parks, clubs, walking trials, and other environments that promote exercise is vital.

This study has some limitations. First, diabetes prevalence and physical inactivity prevalence data were calculated from the BRFSS database, where respondents are 18 years old and older. The lack of children's diabetes data may cause an underestimation in our results. Second, the BRFSS survey does not distinguish between Type I and Type II diabetes mellitus. Third, only data from the 48 contiguous states were included. Data from Hawaii, Alaska, or Puerto Rico are not included in analyses because they are not adjacent to any of the 3,109 counties in the contiguous states, and Markov random fields cannot build up a neighbourhood matrix in those separate areas. However, we believe the exclusion of those areas will not significantly affect our findings because data from the excluded areas do not have a significant spatial correlation with the 48 contiguous states. Fourth, using a spatial interactive term in Model IV and Model V may not provide a better model fitting compared to the linear model, while it is a trade-off for investigating geographic disparities in a mediator analysis. Fifth, we proposed a spatiotemporal approach to carry out a mediator analysis, which originally makes all of the standard assumptions of the general linear model. The sample size of this study is large enough to exempt the normality assumption, but we still suggest future studies with a small sample size pay attention to model assumptions and use the STAR model if necessary.

Conclusions

In conclusion, this study investigated the role physical inactivity plays as mediator in the relationship between diabetes and poverty. National or regional health policies need to promote diabetes prevention by increasing the amount of physical activity in vulnerable populations. While the benefits of physical activity and diabetes prevention are known, people face barriers such as cost or inadequate infrastructure to support physical activity. Changing health behaviour requires personal commitment and reduction of barriers. Hence, when stakeholders take action to increase physical activity at global, regional and local levels, a priority in interventions will be providing low-cost access to physical activity, especially in lower income communities.

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