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Original article

Racial differences in spatial patterns for poor glycemic control in the Southeastern United States

Rebekah J. Walker, PhD [a, b], Brian Neelon, PhD [c, d], Melanie Davis, PhD [c, d], Leonard E. Egede, MD, MS [a, b, *]

[a] Division of General Internal Medicine, Department of Medicine, Medical College of Wisconsin, Milwaukee
[b] Center for Patient Care and Outcomes Research (PCOR), Medical College of Wisconsin, Milwaukee
[c] Health Equity and Rural Outreach Innovation Center (HEROIC), Ralph H. Johnson Veterans Affairs Medical Center, Charleston, SC
[d] Department of Public Health Sciences, Medical University of South Carolina, Charleston

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ABSTRACT

Purpose: Evidence consistently shows poor outcomes in racial minorities, but there is limited understanding of differences that are explained by spatial variation. The goal of this analysis was to examine contribution of spatial patterns on disparities in diabetes outcomes in the Southeastern United States.
Methods: Data on 64,022 non-Hispanic black (NHB) and non-Hispanic white (NHW) veterans with diabetes living in Georgia, Alabama, and South Carolina were analyzed for 2014. Hemoglobin A1c (HbA1c) was categorized as controlled (less than 8%) and uncontrolled (greater than or equal to 8%). Logistic regression was used to understand the additional explanatory capability of spatial random effects over covariates such as demographics, service connectedness, and comorbidities. Data aggregated at the county level were used to identify hotspots in distribution of uncontrolled HbA1c and tested using local Moran's I test.
Results: Overall percent uncontrolled HbA1c was 36.5% (40.8% in NHB and 33.4% in NHW). In unadjusted analyses, NHB had 37% higher odds of uncontrolled HbA1c (odds ratio [OR]: 1.37, 95% confidence interval, 1.32, 1.41). After adjusting for demographics and comorbidities, the OR decreased to 1.09 but remained significant (95% confidence interval, 1.05, 1.13). The OR further decreased after incorporating spatial effects (OR: 1.07, 95% confidence interval, 1.03, 1.11) but remained statistically significant. Hotspots of high HbA1c were detected, and spatial patterns differed across racial groups.
Conclusions: Differences in spatial patterns in glycemic control exists between NHB and NHW veterans with type 2 diabetes. Incorporating spatial effects helps explain more of the disparity in uncontrolled HbA1c than adjusting only for demographics and comorbidities, but significant differences in uncontrolled HbA1c remained.

Diabetes is the seventh leading cause of death in the United States and is associated with significant morbidity, mortality, and health care utilization and cost, including among veterans [1–4]. Complications can be minimized and mortality lowered with improved glycemic control; however, national estimates suggest nearly half of those with diabetes do not meet national targets [5,6]. Evidence consistently shows racial minorities have higher prevalence of diabetes, worse diabetes outcomes, higher risk of complications, worse glycemic control, and higher mortality rates compared to non-Hispanic whites (NHWs), including an equal access system like the Veterans Health Administration (VA) [1,7–13].

Residential segregation is considered one of the fundamental causes of racial disparities in health, and patients with diabetes are particularly at risk for neighborhood influences because of the impact of social norms and values, physical attributes, and availability of resources on self-management behaviors necessary to maintain good glycemic control [14–20]. Most work on neighborhood influence has focused on controlling for region or rural/urban residence [12,15,21–23]. However, there is limited attention to how spatial patterns impact outcomes in diabetes. Spatial patterns can help in visualizing mismatch in health care supply and demand, as well as in determining areas with excess disease prevalence, to

* Corresponding author. Division of General Internal Medicine, Department of Medicine, Medical College of Wisconsin, 8701 Watertown Plank Rd, Milwaukee, WI 53226. Tel.: +1-414-805-0840; fax: +1-414-805-0855.
E-mail address: legede@mcw.edu (L.E. Egede).

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better elucidate the impact of residential segregation on health [24–26]. Therefore, use of methodologies that integrate spatial patterns can help decision makers understand underlying patterns of disease attributable to environmental factors structurally determined by race, identify areas where organizational factors influence outcomes, and better plan health interventions tailored to local needs [24–26].

Recent advances in Geographic Information Systems to visualize patterns and spatial analysis provide novel strategies to examine spatial variations; however, these novel tools are underutilized [24,27]. Therefore, the goal of this analysis was to better understand the contribution of spatial patterns on disparities in diabetes outcomes in the Southeastern United States.

Research design and methods

Data source and sample

A national cohort of veterans with type 2 diabetes was created using administrative data from the VA. Veterans with two or more International Classification of Diseases Ninth Revision codes for diabetes (250.xx) in either inpatient or outpatient visits in 2014 were retrieved. Individuals whose residential address was within the 272 counties in Georgia, Alabama, and South Carolina were selected for analysis. Race was derived using the patient race and ethnicity files and considered to be NHB if there was any record of indication of this category. For the purpose of this analysis, only NHB and NHW patients were selected. Laboratory values for hemoglobin A1c (HbA1c) measures were linked using scrambled social security numbers. Individuals missing HbA1c values were not included in the analysis, resulting in a final sample size of 64,022.

County was used as the unit of analysis for two reasons. First, from a policy standpoint, county was readily available in the electronic medical record and is the measure of location used to define VA catchment areas, therefore matching differences among patients who use the same health care facility. Policy decisions within the VA are likely to be made at a regional rather than neighborhood level, and therefore, for the purposes of this, VA-based analysis county level differences are reasonable to consider. Second, from a methodological standpoint to allow analysis of three states and maintain a reasonable number of spatial effects while fitting the model, county was an appropriate spatial unit.

Study variables

The primary outcome variable was glycemic control (HbA1c) dichotomized as controlled (less than 8%, less than 64 mmol per mol) or uncontrolled (greater than or equal to 8%, greater than or equal to 64 mmol per mol). A cutoff of 8% was chosen based on VA clinical guidelines [28]. Therefore, for the purposes of this analysis, veterans with an HbA1c between 7% and 8%, who would be considered not well controlled by American Diabetes Association guidelines, were considered controlled by VA guidelines [28,29]. The primary independent variable for logistic regression models was race dichotomized into NHB or NHW. Covariates included in adjusted analyses were age, gender, marital status, service-connected disability level, rural/urban residence, median household income, and comorbidities. Marital status was defined as married or single. Service connected disability was categorized as less than 50% or greater than or equal to 50%, representing the cut point for veterans being exempted from copayments for treatment at VA medical centers. Location of residence was categorized as urban, rural, or highly rural using rural urban commuting area codes [30]. Median household income at the county level was determined based on census data and included to adjust for socioeconomic status [31]. Individual level income data were not available in the data set. Comorbidities were based on International Classification of Diseases Ninth Revision codes and included substance abuse, anemia, cancer, cerebrovascular disease, congestive heart failure, cardiovascular disease, depression, hypertension, hyperthyroidism, liver disease, lung conditions, electrolyte disease, obesity, psychoses, peripheral vascular disease, and other diseases [32].

Statistical analysis

Three analyses were performed on individual level data: unadjusted, covariate adjusted, and covariate adjusted + spatial random effect analyses. For unadjusted analyses, we used a logistic regression model that regressed uncontrolled HbA1c on one variable (race). Second, a similar model was fit including sociodemographic and comorbidity covariates. Third, we constructed a model that not only included the covariates of the second model but also incorporated a hierarchical spatial random effect for county. The spatial random effect was assigned a conditional autoregressive prior in a Bayesian setting to allow for borrowing of information across adjacent counties and spatial "smoothing." The model was fit in R-INLA (http://www.r-inla.org/), a package that allows for integrated nested Laplace approximation to derive posterior estimates in a Bayesian framework [33].

Maps of the distribution of uncontrolled HbA1c aggregated at the county level were created using ESRI Geographic Information System [34]. To identify hotspots, a local Moran's I test was conducted [35]. "High-high" hotspots were identified as neighboring counties with a positive standardized percent of uncontrolled A1c, a positive standardized spatial lag, and a significant local Moran's statistic. These areas represent localized clusters of above-average uncontrolled HbA1c. Likewise, "low-low" hotspots were identified as county clusters with a negative standardized percent of uncontrolled A1c, a negative standardized spatial lag, and a significant local Moran's statistic. These areas represent localized hotspots of controlled HbA1c. Analysis was run first on the full sample and then by race to compare spatial patterns by NHB and NHW veterans. Local Indicators of Spatial Association maps were used to display information [35]. SAS was used to manage and aggregate data and R.3.2.2 was used to compile maps [36].

Results

Sample sizes per county ranged from $n = 5$ to $n = 2409$ (mean = 235, median = 108). Percent uncontrolled HbA1c ranged from 18% to 100% across counties (mean = 37.74%, median = 37.36%). Table 1 shows the baseline characteristics of the study subjects overall and by racial category. Differences existed in rural/urban residence with 70.3% of NHB living in urban areas, compared to 52.2% of NHW. Overall percent uncontrolled HbA1c defined as HbA1c greater than or equal to 8% was 36.5 (40.8% in NHB and 33.4% in NHW).

Table 2 shows the unadjusted, covariate adjusted, and covariate plus spatially adjusted odds ratios [ORs]. In unadjusted analyses, NHB had 37% higher odds of uncontrolled HbA1c (OR: 1.37, 95% confidence interval [CI], 1.32, 1.41). After adjusting for demographics and comorbidities, the OR decreased to 1.09, but remained significant (95% CI, 1.05, 1.13). The OR further decreased after incorporating spatial effects (OR: 1.07, 95% CI, 1.03, 1.11), but remained statistically significant.

Figure 1 shows the maps of percent uncontrolled diabetes and Figure 2 shows the Local Indicators of Spatial Association maps indicating hotspots of uncontrolled diabetes. Maps indicate different spatial patterns for NHW and NHB veterans. It is

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