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RESEARCH ARTICLE

The Impact of Social Determinants of Health on Hospitalization in the Veterans Health Administration

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Introduction: This study aims to assess the effect of individual and geographic-level social determinants of health on risk of hospitalization in the Veterans Health Administration primary care clinics known as the Patient Aligned Care Team.

Methods: For a population of Veterans enrolled in the primary care clinics, the study team extracted patient-level characteristics and healthcare utilization records from 2015 Veterans Health Administration electronic health record data. They also collected census data on social determinants of health factors for all U.S. census tracts. They used generalized estimating equation modeling and a spatial-based GIS analysis to assess the role of key social determinants of health on hospitalization. Data analysis was completed in 2018.

Results: A total of 6.63% of the Veterans Health Administration population was hospitalized during 2015. Most of the hospitalized patients were male (93.40%) and white (68.80%); the mean age was 64.5 years. In the generalized estimating equation model, white Veterans had a 15% decreased odds of hospitalization compared with non-white Veterans. After controlling for patient-level characteristics, Veterans residing in census tracts with the higher neighborhood SES index experienced decreased odds of hospitalization. A spatial-based analysis presented variations in the hospitalization rate across the Veterans Health Administration primary care clinics and identified the clinic sites with an elevated risk of hospitalization (hotspots) compared with other clinics across the country.

Conclusions: By linking patient and population-level data at a geographic level, social determinants of health assessments can help with designing population health interventions and identifying features leading to potentially unnecessary hospitalization in selected geographic areas that appear to be outliers.

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INTRODUCTION

Social determinants of health (SDOH), characterized by behavioral, social, economic, environmental, and occupational factors, are powerful drivers of the well-being of individuals and communities.[1] Value-based programs (i.e., pay-for-performance, quality incentive programs, and risk-based alternative payment models, such as bundled payments and accountable care organizations) offer financial incentives to U.S. healthcare providers to improve the quality of care while reducing healthcare costs.[2,3] Thus, when measuring quality of care and calculating payments, it will be essential to assess SDOH in relation with clinical factors. Otherwise,

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differences in patient characteristics may affect healthcare outcomes and costs independently of variations in the provision of care.[2,4,5]

Currently, most healthcare analytics, predictive-modeling tools, and payment adjustments lack information on SDOH risk factors, the context, and characteristics of the patient's community of residence. The analytics typically include only certain demographic and clinical characteristics (e.g., age, sex, and clinical comorbidities).[2,6] Adjustment for SDOH factors using data from both the patient's record and their neighborhood can help to identify those with socioeconomic and behavioral challenges. In addition, spatial analyses of communities could identify areas of significant increased risk and allow for community-level prevention and intervention efforts.[6−11]

As one of the largest integrated health systems in the country, the Veterans Health Administration (VHA) is increasingly interested in the development of predictive modeling tools and population health indicators that take into account SDOH factors of the Veterans and those associated with their communities. Unlike most medical providers, the VHA has a statutory commitment to address both the medical and non-medical needs of their patients.[12−14] The VHA is organized into 21 geographic regions termed *Veteran Integrated Service Networks* (VISNs). The VHA provides primary care to more than 5 million Veterans at 933 hospital-based or community-based clinics nationwide, which are operated by either the VHA or contractors. Every clinic has implemented the patient-centered medical home model of care, known in the VHA as the Patient Aligned Care Team program.

The study team used patient-level electronic health record (EHR) data from the VHA's VistA system[15] to assess the association between individual and geographic-level SDOH and the risk of hospitalization. The team also applied GIS methods to visualize the national distribution of hospitalizations in relation to primary care clinics. A spatial cluster detection is performed to identify hotspots of increased risk of hospitalization, while accounting for the heterogeneous distribution of the VHA population nationwide.

METHODS

Study Population

The study team obtained data on hospitalizations (overnight stay in a VHA hospital) in 2015 from Veterans with at least one primary care clinic visit during the year and a unique identification number assigned by the VHA. For patient-level information on age, sex, race, Gagne comorbidity score,[16] and census tract, Federal Information Processing Standards code data were collected from VHA's Corporate Data Warehouse,[17] which incorporates various VHA databases, including VistA.[15]

Measures

The Gagne comorbidity score combines the Charlson and Elixhauser measures to predict short- and long-term mortality (with a higher numerical score predicting higher risk of death).[16] To assess SDOH factors on a population level, they calculated a neighborhood SES (NSES) index[18] using the American Community Survey (2011−2015, 5-year estimate)[19] data on a census tract level. The NSES[18] index, validated for VHA patient population in previous studies,[13] was a summary measure of six geographic-level census-based variables that linked to the census tract of a participant's residence. The summary measure ranged from 0 to 100, with higher values corresponding to higher SES. The measure variables included: (1) percentage of adults aged ≥25 years with less than high school education, (2) percentage of males who were unemployed, (3) percentage of household incomes below the poverty level, (4) percentage of households receiving public assistance, (5) percentage of households with children in which the head of household was female, and (6) median household income. They calculated the NSES index by computing a z-score for each variable by subtracting the population mean and then dividing it by the population SD. They then subtracted the z-scores for the first five components from that of the median household income and scaled the results to the 0−100 range.[13,18] The IRB of Johns Hopkins Bloomberg School of Public Health approved this study.

Statistical Analysis

The study team performed univariate analyses for each of the different factors associated with hospitalization among VHA primary care patients in 2015. For multivariable analyses, they applied logistic regression using generalized estimating equation models with robust variance.[20] The multivariable model had patient-level variables for age (years), sex, race (white versus nonwhite), and Gagne comorbidity score. They included NSES as a group or cluster-level variable because it was measured on the census tract level. The multivariable model adjusted for the effect of the geographically clustered data in the NSES index when assessing the association between hospitalizations and patient and population-level characteristics.[21] The authors conducted all analyses in 2018 in R, version 3.3.1 (using the generalized estimating equation package for modeling) and used the ArcGIS software, version 10.6 to generate the geographic maps.

For the spatial exploratory data analysis, they first mapped the prevalence of hospitalization for Veterans receiving care at a VHA primary care clinic located in the 48 conterminous U.S.[10] They then estimated the catchment areas based on the VHA primary care clinics (hospital-based or community-based clinics) using Theissen polygons,[22] as only longitude and latitude of the clinic locations were available. The catchment areas reflected the geographic areas closest to each clinic and assumed that each Veteran visited the VHA primary care clinic that was closest to them. The authors linked patient-level data to the respective clinics with the VHA assigned identification number. Also, the authors treated hospitalization as binary (any hospitalization in 2015) and aggregated the number for each clinic (numerator). The number of patients per clinic was used as the population at risk (denominator).

The study authors then assessed spatial clustering and identified hotspots of hospitalization across the primary care clinics on the map, using the Kulldorff spatial scan method of cluster detection (SaTScan, SpatialEpi package in R, version 3.3.1).[9] They used a purely spatial Poisson model for the hospitalization count per population at risk for each primary care clinic. They defined the maximum population at risk for a cluster as <50%. The most likely clusters were determined as those with the highest maximum likelihood value calculated using 999 Monte Carlo replications.[9] Statistical significance for all cluster analyses used an α of 0.05. The model calculated the observed number of hospitalized cases per population in each clinic over the expected number under the null hypothesis of complete spatial homogeneity; RR hospitalization for regions reported.

The study team adjusted the cluster detection analysis for race (white and non-white) and Gagne comorbidity score (categorized as high and low based on the median value of the score), but not for age, because having adjusted other factors in the multivariable model, age turned out not to have an impact on hospitalization (OR=1; Table 1). The data set contained ≅92% males and 8% females, so the authors restricted the cluster detection to male Veterans only. Using NSES index quartiles, the authors analyzed cluster detection of stratified hospitalization, which is consistent with recommendations from the National Academy of Medicine.[2] The resulting cluster detection maps were used to assess hospitalization in primary care clinics that serve patients with similar socioeconomic characteristics and barriers.

RESULTS

The 2015 hospitalization rate for VHA Veterans in primary care clinics was 6.63%. Most of the hospitalized Veterans were male (93.40%) and white (68.80%); the mean age was 64.5 years (Table 1). The demographic data had a high completeness rate, with <1% of data missing among the entire Veteran population.

In the multivariable analysis, male Veterans had 17% increased odds of hospitalization compared with female Veterans, and white Veterans had 15% decreased odds of hospitalization compared with non-white Veterans (Table 1). After accounting for patient-level characteristics, Veterans residing in census tracts with a higher

Table 1. The Analysis of Factors Affecting Hospitalization Among Veterans at VHA Primary Care Clinics in 2015

Factor	Yes	No
Univariate analysis[a]		
Hospitalization, *n* (%)	360,527 (6.63)	5,080,516 (93.38)
Age, years, M (SD)	64.46 (13.86)	62.7 (16.5)
Sex (row %)		
Male	6.71	93.29
Female	5.65	94.35
Race (row %)		
White	6.25	93.75
Non-white	7.72	92.28
Black	8.40	91.63
Hispanic	6.66	93.34
Native American/Alaskan	8.05	91.95
American Samoan/Pacific Islander	2.38	97.61
Asian	3.32	96.67
Native Hawaiian/Pacific Islander	5.01	94.99
Multiracial	9.23	90.77
Gagne comorbidity score,[b] M (SD)	2.07 (2.07)	0.33 (1.24)
NSES index, M (SD)	0.67 (0.11)	0.69 (0.1)
GEE modeling,[a] (OR/SE)		
Age, years	1.00	1.00
Sex (female as reference)	1.17	1.01
Reported race (non-white as reference)	0.85	1.00
Gagne score[b] (low as reference)	3.33	1.00
NSES index (1st quartile as reference)		
2nd quartile	0.80	1.00
3rd quartile	0.71	1.00
4th quartile	0.64	1.01

[a]All *p*-values <0.001.
[b]Gagne comorbidity score is a single numerical comorbidity score for predicting short- and long-term mortality, constructed by combining conditions in the Charlson and Elixhauser measures. Higher score predicts higher risk of death.
GEE, generalized estimating equation; NSES, neighborhood SES (the higher NSES represents a better SES); VHA, Veterans Health Administration.

NSES index had decreased odds of hospitalization. For example, Veterans residing in census tracts with a second quartile NSES index had 20% decreased odds of hospitalization compared with those residing in census tracts with a first quartile NSES index (lowest SES). The odds of hospitalization decreased with each quartile increase of the NSES index (Table 1).

Figure 1 illustrates the prevalence of hospitalization for the VHA population in 2015 for primary care clinics in the 48 contiguous states. The prevalence of hospitalization was 7.55% and higher at several of the primary care clinics in the southern VISNs and those in the West (Figure 1, dark red). At a smaller number of primary care clinics in the Midwest and Northeast VISNs, the prevalence of hospitalization was ≥7.55%.

Cluster detection analyses, stratified for quartiles of NSES index and adjusted for race and Gagne comorbidity score, showed spatial variation in clusters of increased risk for hospitalization (Figure 2).[2] Overall, the analysis detected consistently high-risk clusters in areas along the Appalachian Mountain region going north and south.

For clinics containing census tracts with the lowest quartile of NSES within their catchment area (Figure 2A), the analysis identified several clusters with increased risk of hospitalization (RR, 1.25−1.37, light green) throughout the Midwest, East, and a smaller area in the West. There were smaller clusters of higher risk of hospitalization in the South (RR, 1.38−1.56, light orange) and a primary care clinic with high risk of hospitalization (RR, 1.56−1.90, dark orange) in Northeast.

Risk of hospitalization among clinics containing census tracts with an NSES index of 0.25−0.50 within their catchment area was fairly evenly distributed (RR of up to 1.33,

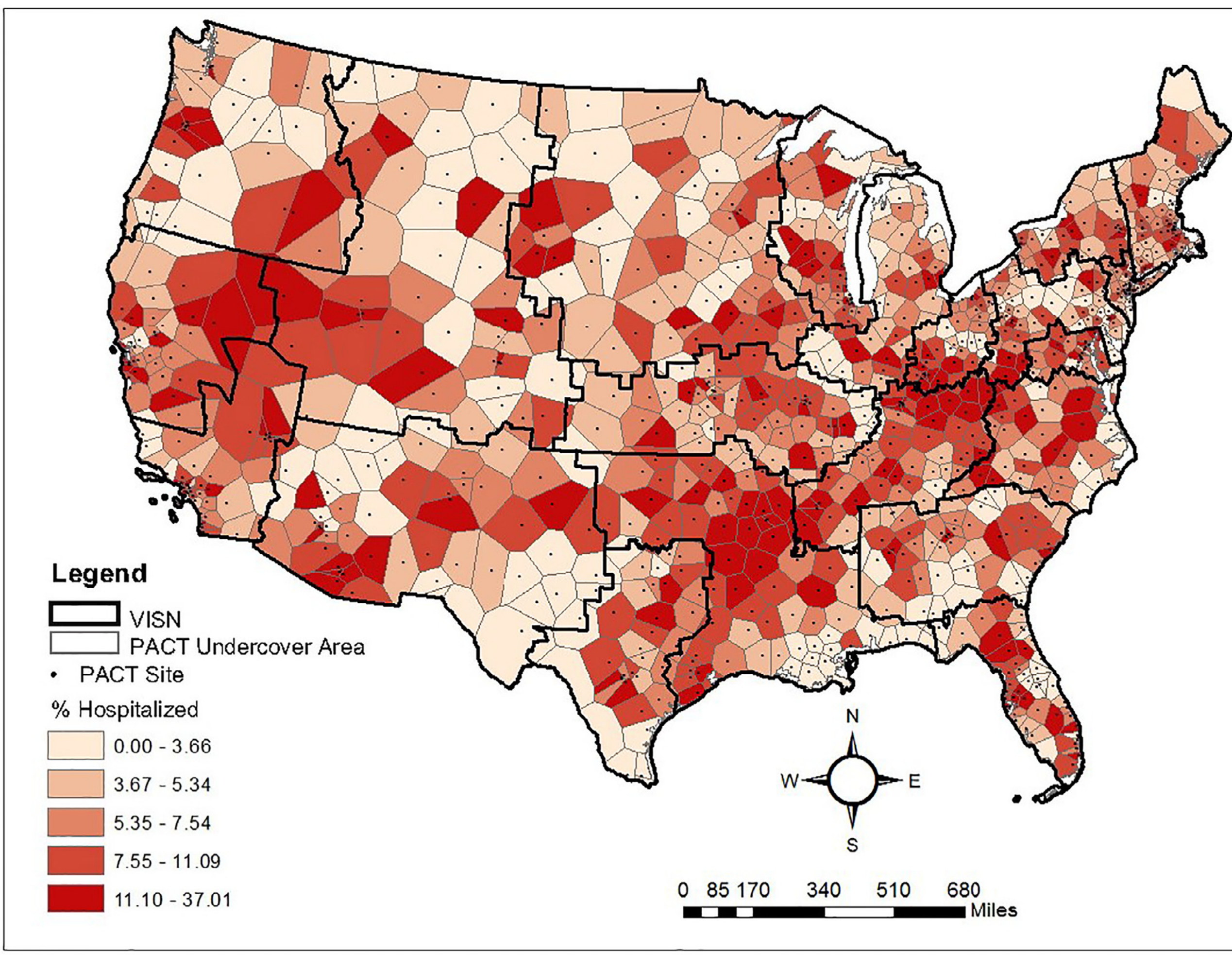

Figure 1. Unadjusted hospitalization rate among VHA population across the primary care clinics (PACT sites) and VISNs in 2015.
Note: Hospitalization is reported as an overnight stay in a VHA hospital only and estimated for the geographic catchment area of each primary care clinic. PACT, patient-aligned care team; VHA, Veterans Health Administration; VISN, Veterans Integrated Service Networks.

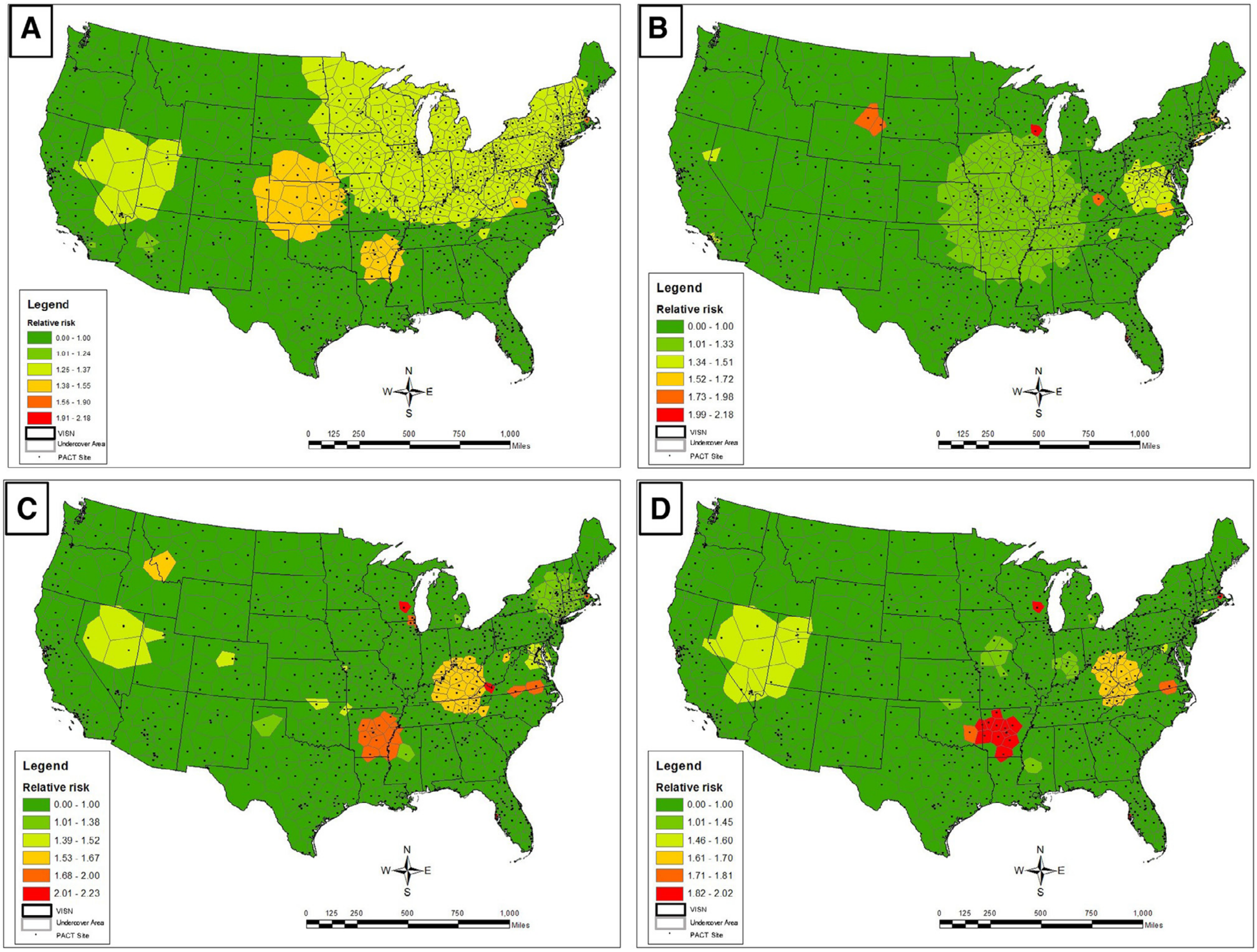

Figure 2. Hospitalization cluster detection for male Veterans seeking care at the VHA primary care clinics (PACT sites) in 2015, controlling for race and Gagne comorbidity score with stratification for the NSES index by quartiles. (A) Quartile 1: lowest quartile, (B) Quartile 2: 0.25−0.50, (C) Quartile 3: 0.50−0.75, (D) Quartile 4: highest quartile.

Note: Hospitalization is reported as an overnight stay in a VHA hospital only and estimated for the geographic catchment area of each primary care clinic. Appendix Table 1 (available online) presents the characteristics of clusters with high risk of hospitalization across NSES index quartiles.
PACT, patient aligned care team; NSES, neighborhood SES; VHA, Veterans Health Administration.

two shades of dark green), although the analysis detected a cluster with higher risk of hospitalization (RR, 1.34−1.51, light green) in Virginia, West Virginia, Maryland, and Southern Pennsylvania, and two primary care clinics in North Carolina and Nevada (Figure 2B). Primary care clinics in Virginia, New York, Connecticut, and Massachusetts had a higher risk of hospitalization (RR, 1.52−1.72, light orange), whereas those in Wyoming, Wisconsin, and Kentucky (RR, 1.99−2.18) had the highest risk.

For those clinics containing census tracts with an NSES index of 0.50−0.75 (Figure 2C) and the highest quartile of NSES (Figure 2D) within their catchment area, there was minimal variation in the risk of hospitalization (RR of up to 1.38 for the third NSES quartile and RR of up to 1.45 for the highest quartile). The analysis detected a few higher risk clusters in the Midwest, South, and West, particularly in Arkansas, for both third and highest NSES quartile (RR, 1.68−2.00 and RR, 1.82−2.02, respectively).

DISCUSSION

This study assessed the distribution of hospitalization across VHA primary care clinics and identified associations with Veterans' socioeconomic factors. Overall, the prevalence of hospitalization was slightly lower than the national prevalence (6.63% in study population versus 7.60% nationally).[23]

The multivariable modeling took into account a number of patient-level characteristics, allowing the assessment of the impact of population-level characteristics on the census tract level. In line with previous studies of the VHA population, this study found that nonwhite Veterans had higher odds of being hospitalized. This association held after adjustment for patient-level and neighborhood characteristics.[11,24,25]

The evidence varies on the impact of including SES data for assessment of the health outcomes. A number of prior studies found that including data on different social factors would improve prediction of health outcomes, such as hospitalization and readmission risk.[6,24,25] For instance, Hu et al.[6] assessed various socioeconomic factors influencing readmissions within 30 days after discharge in an urban teaching hospital (Henry Ford Hospital, an 802-bed teaching hospital in Detroit, Michigan) and showed that those patients living in high-poverty neighborhoods had 24% more readmission risk than other patients. Also, Nagasako and colleagues[26] showed that SES data would narrow down the range of observed variations in readmission rates. By contrast, Bhavsar et al.[27] assessed the value of NSES in predicting the risk of adverse outcomes in EHR-based risk models, but did not find NSES contributing much more to risk prediction beyond demographic (e.g., age and race) and insurance data already provided in the EHR. This study applied a different approach and followed the recommendations from the National Academy of Medicine[2] to stratify risk of hospitalization using NSES index quartiles in the multivariable model. The model suggests that Veterans residing in census tracts within the top three (second, third, and fourth) quartiles of NSES index had 20%, 29%, 36% lower odds, respectively, of hospitalization compared with those residing in census tracts with first (lowest) quartile of NSES index.[6,24,25]

Using spatial cluster detection, this study found that the prevalence of hospitalization was higher for several of the primary care clinics in the southern VISNs and those in the West. This finding was similar to the risk-standardized hospitalization for Medicare enrollees in 2013, with higher hospitalization rates in the Midwest and South.[28] The age distribution of the study population was comparable with the Medicare enrollees.

This study provided similar results to previously published geographic distribution of health outcomes among Veterans. Krishnamurthi and colleagues[11] assessed geographic variations for leading causes of cardiovascular hospitalization in 8.45 million U.S. Veterans and presented relatively similar distribution to this study with higher hospitalization rates mainly among those Veterans residing in the South and West.

There is a significant amount of heterogeneity in the population density across the U.S. The study team applied a Poisson spatial cluster detection using the Kulldorff method,[9] accounting for the population at risk within the catchment area of each primary care clinic. The cluster detection identified high-risk clusters of hospitalization for NSES index quartiles, while accounting for the potential confounders. Cluster detection maps supported the findings from the multivariable model and showed evidence of geographic heterogeneity in risk of hospitalization in some regions of the U.S. They presented different geographic patterns for NSES quartiles and from the overall national patterns of hospitalization. For instance, clusters of primary care clinics with very high risk of hospitalization (clusters with shades of dark orange and red) were detected in different sizes and geographic areas for primary care clinics containing census tracts with higher quartiles of NSES compared with those with lower quartiles of NSES. The analysis identified primary care clinics whose risk of hospitalization was high for all quartiles of NSES, which may reflect structural problems in their care delivery. Similarly, areas with low risk of hospitalization across all quartiles of NSES may be studied as part of a future analysis to determine what structural characteristics make the primary care clinics more able to provide high-quality care. Further analysis on the underlying heterogeneity in the clusters should be explored but is beyond the scope of this paper.

The data in this study were unique and contained information on more than 5 million Veterans during the year of study. Access to the longitude and latitude of the clinic locations made it possible to link the patient-level data to the NSES calculated from the American Community Survey data.[19] This geocoded data allowed detection of spatial patterns for the entire study population.

To the authors' knowledge, this is the first assessment of the national geographic patterns of hospitalization among Veterans in VHA primary care clinics in association with the characteristics of the neighborhoods where the Veterans reside. The approach to include information on the characteristics of Veterans' neighborhoods by stratifying hospitalization based on the NSES index quartiles will help the VHA to identify geographic areas with increased risk of hospitalization for each quartile of the NSES. This approach provides the information needed for resource allocation to improve behavior or the built environment of the Veterans' communities. These findings can guide VHA's development of interventions through their primary care clinics to improve healthcare utilization in targeted neighborhoods. Examples include allocating more funding to those clinics to hire extra staff (considering the challenges of dealing with patients with high social needs) and helping the clinics to get connected to the community-based social services for referral of patients from neighborhoods with low NSES, who suffer from other social needs, such as food or housing insecurity.

These results also help VHA to identify patients from neighborhoods with low NSES index for SDOH screening. And, they provide a roadmap for VHA to perform in-depth performance assessment of primary care clinics that present high risk of hospitalization regardless of the socioeconomic characteristics of their patient population and to plan structural changes in those clinics.

LIMITATIONS

This study had several limitations: (1) The analyses included only Veterans receiving primary care from VHA who were mostly older, white, and male. (2) The hospitalization data only reflected the overnight hospital stay in the VHA facilities and not Veterans' hospitalization in other non-VHA facilities. (3) The population-level characteristics might not accurately reflect an individual's sociodemographic circumstances. (4) Several patient-level and environmental factors not included in this study would likely affect access and utilization of services in primary care clinics across the country (e.g., rural location and availability of transportation), and might have influenced spatial distributions. (5) Primary care clinics varied widely in terms of their characteristics and the characteristics of the Veteran population they served. There were likely some practice-specific variables that impacted hospitalization rate in addition to the individual characteristics of Veterans and geographic locations, as well as the social risk factors measured in this study. (6) Finally, analyzing only 1 year of data did not provide assessment of the temporal pattern of hospitalization.

CONCLUSIONS

These analyses suggest that community-level data, such as those obtained by the U.S. Census Bureau,[19] are a valuable addition to data collected in EHRs and other clinical and administrative patient-level information systems and can help identify patients at risk of poor health outcomes and high social needs. Geographic variations in hospitalization rates based on demographic, clinical, and socioeconomic factors could signal differential access to care and disparities in quality of care, as has been shown in this study.[11] The application of these types of place-based data to assess disparities at the geographic level or other population approaches in health care is a powerful tool to support healthcare policy and allocate resources to "high-need, high-cost" patients and communities.

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SUPPLEMENTAL MATERIAL

Supplemental materials associated with this article can be found in the online version at https://doi.org/10.1016/j.amepre.2018.12.012.

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