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SCIENTIFIC INVESTIGATIONS

Factors impacting sleep center no-show rates after hospital discharge using geospatial coding in Appalachia

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Study Objectives: Screening for early detection of sleep-disordered breathing in hospitalized patients has been shown to reduce readmission rates. However, postdischarge polysomnography for confirmation of diagnosis is required. We analyzed factors for "no-shows" using geospatial techniques.
Methods: Data were obtained between September 2019 and September 2023. The outcome for the study was patients' no-show rate (nonadherent for polysomnography) after hospital discharge. Predictors included the patient's age, sex, body mass index, health literacy, Distressed Communities Index score, and distance to a sleep center for the patient's zip code of residence. Logistic regression was applied to estimate odds of patients' adherence at the patient level using a geospatial mapping technique. Geographically weighted logistic regression was applied to estimate the odds of a zip code's including adherent patients.
Results: Of the 1,318 hospitalized patients established as high-risk for sleep-disordered breathing and referred for an overnight sleep study who were able to be geocoded, 228 were adherent and 1,130 were nonadherent. In nonspatial regression analyses, health literacy (adjusted odds ratio = 1.06; 95% confidence interval = 1.03, 1.09), age (adjusted odds ratio = 0.99; 95% confidence interval = 0.98, 0.99), and drive time (adjusted odds ratio = 0.95; 95% confidence interval = 0.92, 0.97) were identified as statistically significant predictors of patients' adherence. Spatial regression analyses identified areas that had high and low predictive probability of patients' adherence, as well as which community-level factors were co-occurring in those areas.
Conclusions: The findings suggest that both patient-level factors and the community where patients live may impact no-show rates. Health literacy was identified as a key modifiable predictor at the patient level. At the community level, we found that predicted probability of patient adherence varied throughout the state. Efforts should focus on enhancing patients' education at the individual level and understanding geographical factors to improve adherence.
Keywords: sleep health disparities, no-show rate, sleep-disordered breathing, hospital sleep medicine, health literacy, geospatial mapping
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BRIEF STATEMENT
Current Knowledge/Study Rationale: Screening for sleep apnea during hospitalization has been shown to be beneficial in early diagnosis and treatment of the disorder. However, the no-show rate for postdischarge polysomnography remains high in rural Appalachia. To our knowledge geospatial mapping has not been used to determine the reasons for patients' failure to return for polysomnography.
Study Impact: Our findings suggest that whereas distance from a sleep center did influence the no-show rate, health care literacy was a key patient-level modifiable predictor. Understanding key barriers to completion of polysomnography can help health care resource utilization.

INTRODUCTION

Obstructive sleep apnea is a highly prevalent disorder associated with significant cardiovascular implications.[1,2] It is estimated that 80% of obstructive sleep apnea remains undetected.[3] The underdiagnosis of obstructive sleep apnea is particularly prevalent in rural and underserved areas, where access to health care and specialized diagnostic resources is limited.[4] In order to improve early detection and treatment of obstructive sleep apnea, Sharma et al have developed a novel hospital sleep medicine program aimed at screening hospitalized patients for sleep apnea followed by diagnosis and treatment.[5] Early detection and treatment of hospitalized patients has now been shown to improve outcomes including readmissions and emergency room visits and reduce health care use.[6–8] However the "show rate" of positively screened patients to postdischarge polysomnography (PSG) remains low in rural and underserved areas.

There may be several reasons for no-show rates (nonadherence) in a rural and underserved area due to significant health care disparities. However, effective mitigation is only possible if the most important causes can be delineated. Past studies using geospatial techniques have been used to understand aspects of health care disparities that most impact a disease process and appropriate interventions.[9,10] We are not aware of any studies using geospatial analysis to investigate factors that may influence the sleep study no-show rate after hospital discharge (nonadherence) in rural areas.

The purpose of this study was to examine the root causes of suboptimal follow-up of patients identified as high-risk during hospitalization. Using a geospatial technique, we looked at the group of high-risk patients who showed up to the sleep center for their PSG after discharge vs those who did not.

METHODS

Study design

In this observational study, data were obtained retrospectively from patients admitted to the West Virginia University hospital and consulted by the inpatient sleep medicine program from July 2019–September 2023. The hospital sleep medicine program formally screens patients admitted to the adult medical ward for sleep apnea using the STOP questionnaire. Patients who score positive on this screening questionnaire then undergo high-resolution pulse oximetry or apnea link testing followed by consultation with the sleep medicine team. Patients are then counseled on sleep apnea and its potential impact on their comorbid conditions. Patients are advised to undergo diagnostic PSG after discharge. This study was approved by the West Virginia Institutional Review Board (protocol no. 2009120369).

Study measures

Patients' data were extracted from the West Virginia University hospital medical records. Sociodemographic variables include patients' age, race, body mass index (BMI), health literacy score, rurality, community-level socioeconomic distress for the patient's residential zip code, and drive time from the patient's residential zip code to the sleep center location. Due to low sample size in several categories, patients' race was dichotomized as either non-Hispanic White or other. Rurality was determined using the Rural-Urban Community Area codes according to the patient's residential zip code.[11] The primary outcome of interest for this study was patient adherence as measured by their show rate at the sleep center for a PSG.

The US Department of Health and Human Services defines personal health literacy in their new Health People 2030 as the degree to which individuals have the ability to find, understand, and use information and services to inform health-related decisions and actions for themselves and others.[12] Health literacy was measured at the time of admission to the hospital as part of the hospital admission process. A series of questions in which the patient had to rank their confidence with the question from 1–5 (5 being the most confident) were included.[13] The total possible score was 25 and was directly proportional to the level of health literacy.

All patients included in the study were geocoded to their residential zip code and the sleep center was geocoded to its exact location. Using the ArcGIS (ESRI, Redlands, California) rural drive-time tool, we calculated the drive time in minutes from the centroid of the patient's residential zip code to the location of the sleep center.[14] This tool effectively accounts for 1-way roads and avoids illegal turns in order to optimize travel distance over public roads for cars, sports utility vehicles, and other small vehicles.[15] For our analysis, drive time was modeled in 10-minute increments. **Figure 1** displays the drive time to the sleep study center for the state in 30-minute increments.

Community-level economic disadvantage was measured using the Distressed Communities Index (DCI) score, developed by the Economic Innovation Group.[16] The DCI is a composite score based on 7 measures of socioeconomic status: unemployment, education level, poverty rate, job growth, housing vaccines, business establishments, and median income.[17] Each measure of socioeconomic status is weighted equally (compared to its nearest neighbors) and normalized to obtain a raw score. A score of 0 indicates that a community has no distress and a score of 100 indicates severe distress. A DCI score is available for all zip codes with a population of at least 500 and captures 99% of the US population.[17]

Statistical analysis

Descriptive summary statistics of individual-level patient data were reported as mean and standard deviations for normally distributed continuous variables, frequencies, and percentages for categorical variables. We compared baseline differences between individuals who were adherent and those who were nonadherent using the t test for continuous variables and chi-square test for categorical variables. At the individual level, multivariable logistic regression was applied to analyze patients' sleep intervention adherence. Predictors for sleep intervention adherence included patients' age, sex, race, BMI, health literacy, rurality, DCI, and drive time. This is a global model that estimates single coefficient for each of the independent variables for the whole study area but does not account for spatial variation. All individual-level analyses were conducted using R statistical software, version 4.2.1 (R Foundation for Statistical Computing, Vienna, Austria).

At the local level, geographically weighted logistic regression (GWLR) was applied to estimate the odds of a zip code's having an adherent patient. GWLR is an extension of logistic regression that takes into account the spatial location of each observation (zip code) and captures both spatial association and spatial diversity.[18] GWLR models the association between the outcome variable and independent variables for each observation as separate local models.[16] The local models include each individual observation location, as well as neighboring observations, which are determined based on the bandwidth (neighborhood) size.[19,20] The GWLR produces separate estimates for each independent variable for every observation (zip code) in the study. The GWLR model[21] can be expressed as

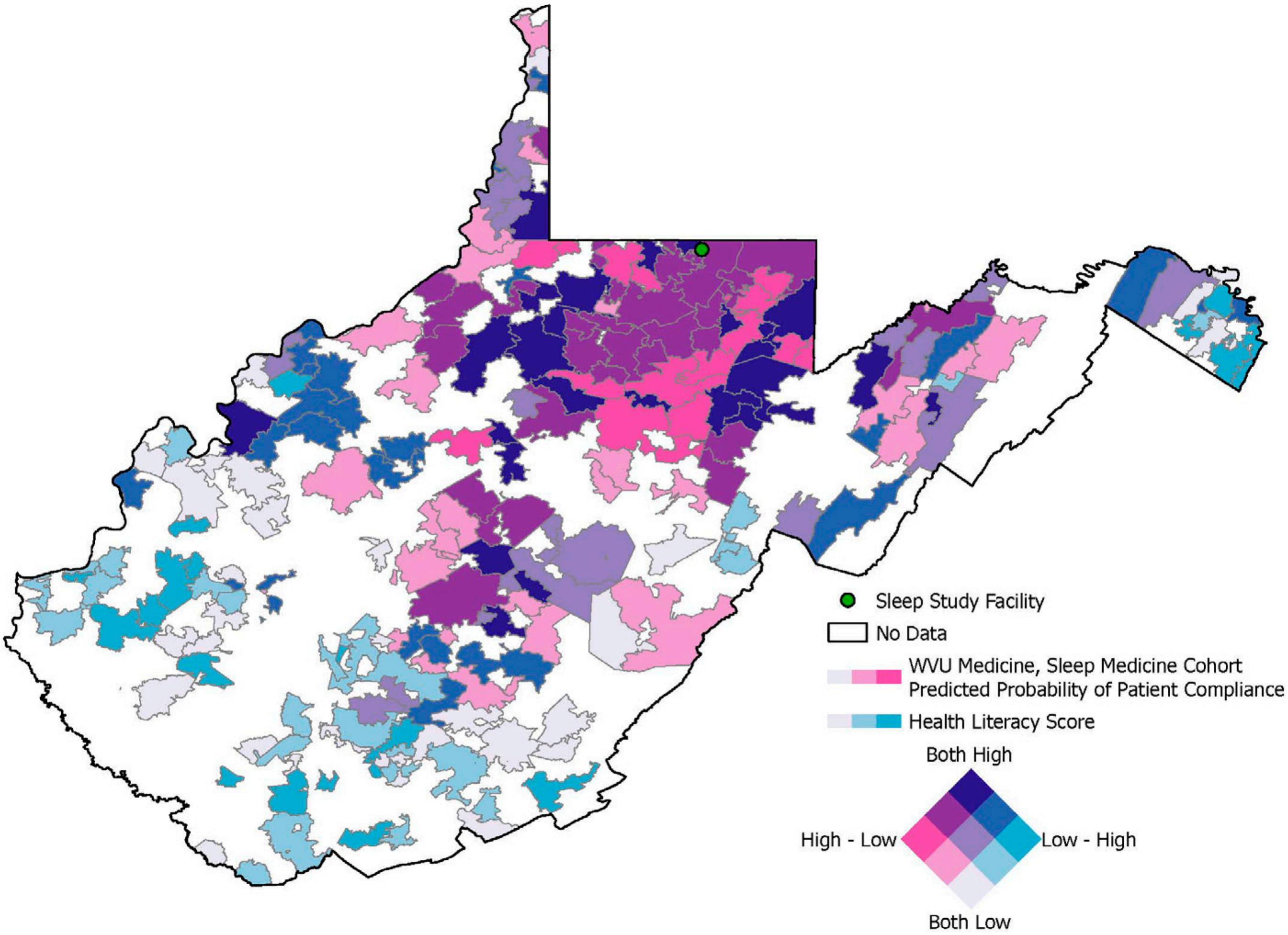
$$log\left(\frac{p_i}{1-p_i}\right) = \beta_{0i}(u_i, v_i) + \sum\nolimits_{j=1}^{k}(\beta_{ij}(u_i, v_i)x_{ij}),$$

where

$$log\left(\frac{p_i}{1-p_i}\right)$$

is the predicted odds of having adherent patients for the ith observation, x_{ij} is a set of independent variables ($j = 1 \ldots k$) for each observation i, (u_i, v_i) is the x,y location of the ith

Figure 1—Relationship between predicted probability and health literacy score.



WVU = West Virginia University.

observation, and $\beta_{ij}(u_i,v_i)$ is the coefficient for jth independent variable for the observation at location i.

For the local study, independent variables of all patients in the study were aggregated to their zip code to adjust for mean patient age, mean patient BMI, percent of the patients who were male, percent of the patients who were non-Hispanic White, mean health literacy score, rurality, DCI score, and drive time. We used an adaptive kernel type and determined the optimal bandwidth size using the golden search option, which automatically determines the number of neighbors for the data based on the Akaike information criterion.[18,19,22] Model diagnostics were analyzed to reduce issues related to multicollinearity and kernel bandwidth selection.[15]

Prediction maps of the probability of a zip code's having a patient be adherent for the sleep study were created by mapping the results of the GWLR model. Bivariate maps showing the relationship between the predicted probability of adherence vs each of the independent variables were created. Spatial analysis and thematic maps were conducted in ArcGIS Pro 2.9.2.[14]

RESULTS

Overall, 2,109 hospitalized patients were identified as high-risk for SBD and referred for an overnight sleep intervention. Of these patients, 791 were excluded due to out-of-state residency or missing information. There were 220 patients (16.69%) who were adherent to the sleep intervention study parameters and 1,098 (83.31%) who were nonadherent to the sleep intervention study parameters (**Table 1**). The patients included in the study were primarily older (mean age: 59.51 ± 13.98 years), obese (mean BMI: 38.77 ± 12.51 kg/m^2) individuals who had an average health literacy score of 20.42 (standard deviation, 6.24) and resided in an area with average DCI score of 20.43 (standard deviation, 6.24). Patients who were adherent were younger, lived in less-distressed communities, were closer to the sleep center location, and were more likely to report higher health literacy scores than patients who were nonadherent There were no significant differences between patient groups regarding BMI, race, and rurality.

Table 1—Sample characteristics of study subjects by adherence.

Variable	Total (1,318)	Adherent (220)	Nonadherent (1,098)	*P*
Health literacy score	20.43 (6.24)	22.07 (6.62)	20.11 (6.11)	<.05
BMI (kg/m^2)	38.77 (12.51)	39.85 (11.15)	38.56 (12.76)	.11
Age (years)	59.51 (13.98)	57.34 (12.75)	59.94 (14.18)	<.05
DCI score	67.33 (23.97)	65.24 (23.82)	67.75 (23.98)	<.05
Drive time (minutes)	79.18 (54.99)	66.32 (50.11)	81.76 (55.58)	<.05
Sex				.45
Male	759 (57.59%)	132 (60%)	627 (57.1%)	
Female	559 (42.41%)	88 (40%)	471 (42.9%)	
Race				.27
Non-Hispanic White	1,216 (92.26%)	207 (94.09%)	1,009 (91.89%)	
Other	102 (7.74%)	13 (5.91%)	89 (8.11%)	
Rurality				.31
Rural	683 (51.82%)	107 (48.64%)	576 (52.46%)	
Urban	635 (48.18%)	113 (51.36%)	522 (47.54%)	

BMI = body mass index, DCI = Distressed Communities Index.

Individual-level multivariable logistic regression

Table 2 presents the odds ratios of patients' adherence for each predictor variable, while controlling for the remaining variables. After adjusting for BMI, age, race, sex, race, rurality, DCI, and drive time, the odds of patients' adherence are expected to increase by 6% for every 1 unit increase in health literacy score (adjusted odds ratio = 1.06; 95% confidence interval = 1.03, 1.09). Conversely, the adjusted odds of patients' adherence decrease by 5% for every 10-minute increase in drive time from the residential zip code to the sleep study center (adjusted odds ratio = 0.95; 95% confidence interval = 0.92, 0.97) and 1% lower for each additional year of age (adjusted odds ratio = 0.99; 95% confidence interval = 0.98, 0.99). There is not enough evidence to conclude that the odds of patient adherence differ based on patient's BMI, sex, race, rurality, and DCI score (**Figure S1**, **Figure S2**, **Figure S3**, **Figure S4**, and **Figure S5** in the supplemental material).

Table 2—Logistic regression of sleep intervention adherence.

Variable	OR	95% CI	*P*
Health literacy score	1.06	1.03–1.09	<.05
BMI	1.01	0.99–1.02	.22
Age	0.99	0.98–0.99	<.05
DCI score	1.00	0.99–1.01	.96
Drive time (10 minutes)	0.95	0.92–0.97	<.05
Male	01.21	0.89–1.64	.22
Non-Hispanic White	1.72	0.96–3.33	.08
Rural	0.95	0.69–1.29	.73

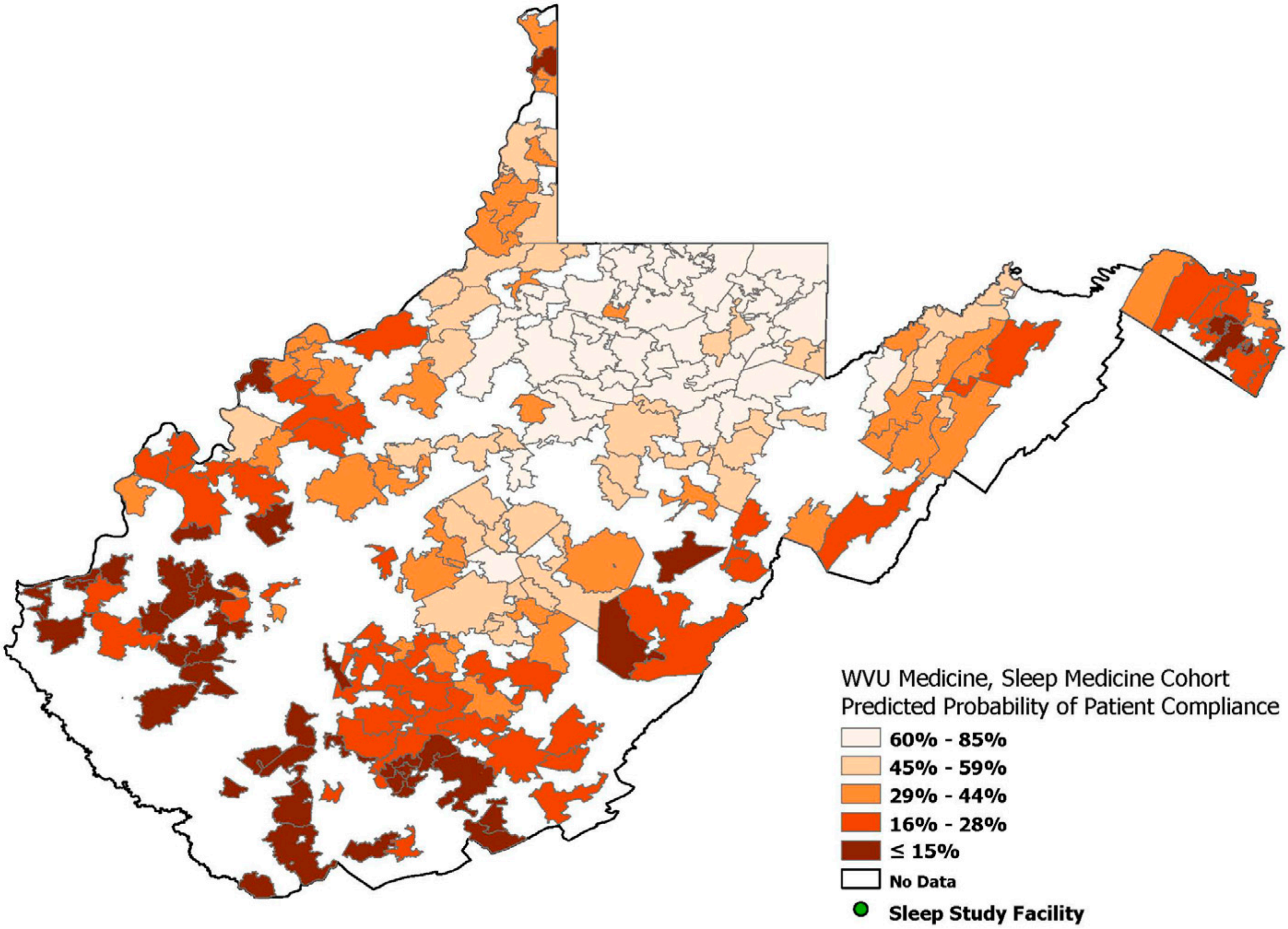
BMI = body mass index, CI = confidence interval, DCI = Distressed Communities Index, OR = odds ratio.

Local-level geographically weighted logistic regression

When patients were geocoded to their residential zip code, the geographic weighted logistic regression showed local areas of high and low predicted probability of sleep intervention adherence (**Figure 2**). More densely populated zip codes in the northern central area of the state had higher percentages (60–84% light-yellow zip codes) of predicted probability of patients' sleep intervention adherence. Meanwhile, more remote zip codes in the southern areas of the state had lower percentages (0–18%, dark-red zip codes) of predicted probability of patients' sleep intervention adherence.

Bivariate maps in **Figure 3** show the relationship between predicted probability of sleep adherence and each of the independent variables. The maps can be interpreted as high sleep adherence as pink, high independent variable score as light blue, high for both as purple, and low for both as light gray. These maps show that levels of health literacy, distressed communities, BMI scores, rurality, sex, race, and age scores are varied throughout the state, as high and low areas of each are seen peppered throughout the state. The majority of the areas that have both low sleep adherence and low health literacy (**Figure 1**), distressed communities, age scores, percent non-Hispanic white, percent male, and BMI scores are in the southern areas of the state and eastern panhandle, which are farthest from the facility (light gray). Conversely, the majority of the areas that have higher sleep adherence but low levels of these variables (pink) are in the north-central, more densely populated areas of the state but are also areas that are closer to the facility. Drive time increased progressively throughout the state as zip codes were further from the facility. **Figure 4** shows that the sleep adherence decreases as drive time to the facility increases, which can be seen with the larger percentage of light blue travel time areas in the southern areas and eastern

Figure 2—Predicted probably of patients' adherence.



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panhandle of the state. There were no specific patterns for rurality and predicted probability throughout the state.

DISCUSSION

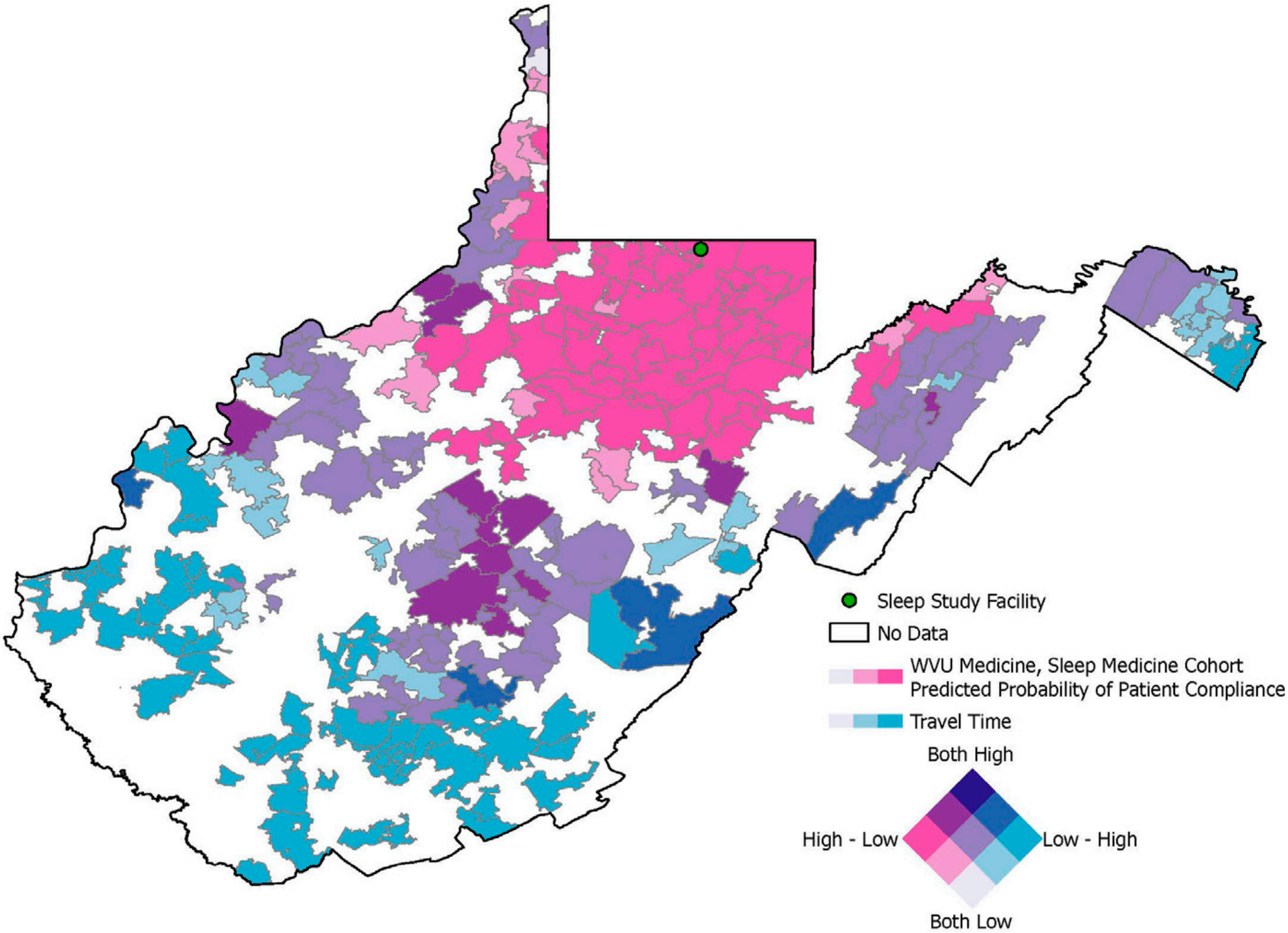
Medical geography has been employed extensively for disease mapping and identifying causes behind clustering of infections.[23] However, with the advent of the computer science revolution, geospatial mapping is being increasingly used to examine health care disparities and allocate resources effectively.[24]

Our study is the first to use geospatial mapping techniques to observe and assess the factors influencing the no-show rate of patients for PSG at the sleep center following hospital discharge. Our study finds that whereas distance was an important barrier for follow-up adherence, personal factors such as low health care literacy and advanced age were also significant factors contributing to poor no-show rate. Additionally, we were able to identify areas that had low predictive probability of patients' adherence and which community level factors were co-occurring in those areas. Rural and underserved Appalachia has many factors that may impede patients' access to health care.[25] Determining the relative influence of each if these may help resource allocation and health care policies targeted to reduce health care disparities.

Sleep heath disparities can have a detrimental effect on overall health.[26] Sleep-disordered breathing is highly prevalent disease, and 80% of cases remain undiagnosed, especially in rural areas.[4,27] Hence, proactive screening for sleep-disordered breathing during hospitalization is becoming an important pathway to target.[5]

The hospital sleep medicine program is a novel program whereby high-risk patients admitted to the medical wards undergo proactive screening for sleep-disordered breathing,[5,28] aiming for early intervention. Prior research suggests that such interventions lead to positive outcomes, including reduction in hospital readmission rates and emergency room visits and lower health care costs.[6,7,29,30] However, in rural and underserved areas, these high-risk patients identified during hospitalization show low postdischarge follow-up rates to the sleep laboratory.[31] Understanding reasons can guide the development of interventions to address these issues and improve outcomes.

Figure 3—Bivariate relationships between predicted probability of sleep adherence and each independent variable.



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Integrating geospatial data with hospital sleep medicine may enhance adherence by targeting main reasons for no-shows.

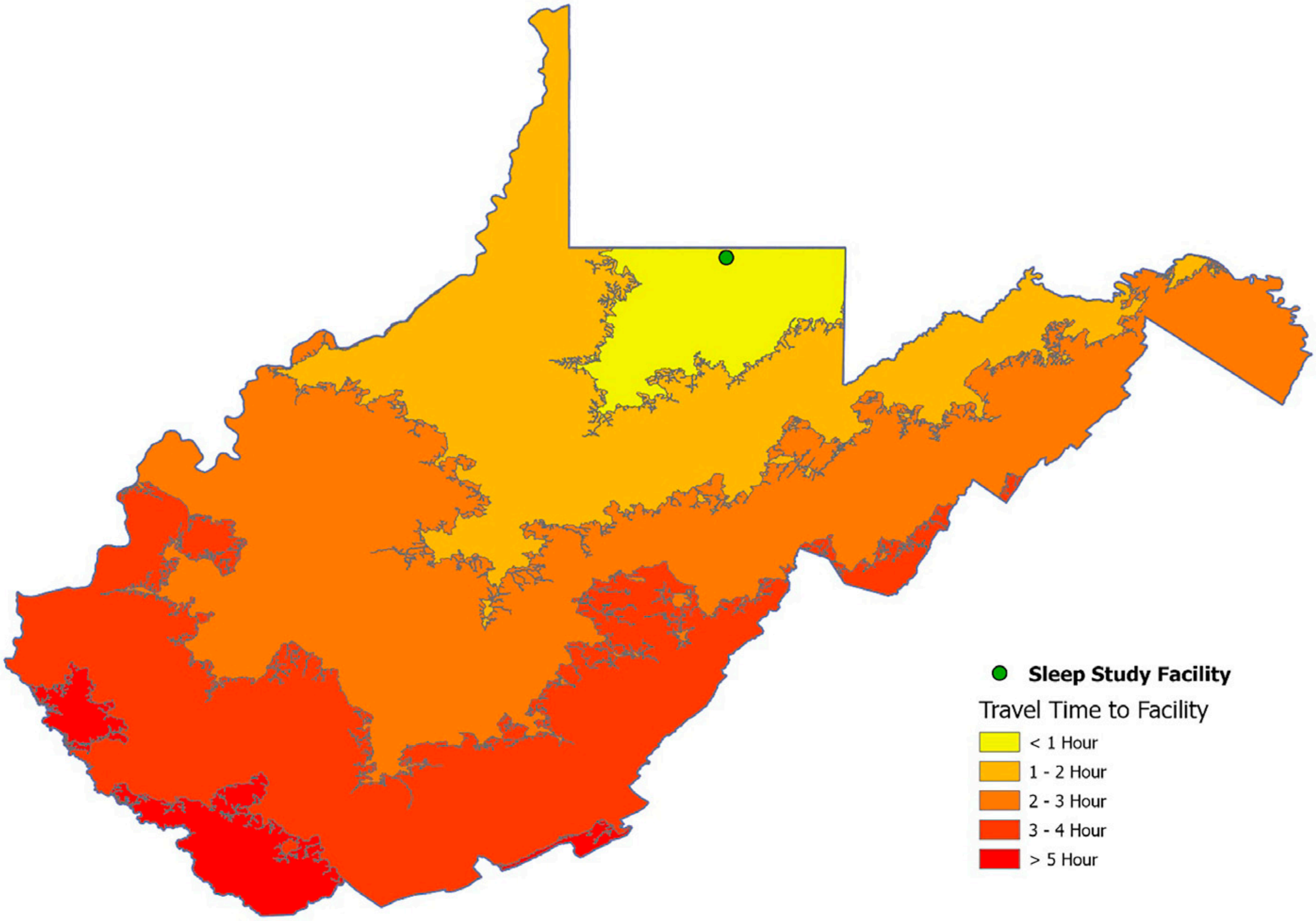
The observation that patient health care literacy is a significant factor in the predicting patient adherence with completing a PSG has important implications. In a resource-limited environment, knowing where to direct efforts are of supreme importance. Our study suggests that patient education and counseling may be the alternative investment instead of opening more sleep laboratories. The Institute of Medicine has designated heath literacy as a crucial national priority for enhancing health care quality.[1] Physicians commonly overestimate patients' literacy levels, which is often a source of health care disparities.[32] There are models of care that may address means to improve health care literacy by active physician and organizational engagement.[33]

Regarding community distress, our study showed that more distressed communities co-occurred in areas with less predicted probability of adherence. This could suggest that community-level disparities such as poverty, overall education, access to care, and more may impact a patient's ability to comply with postdischarge instructions. Ultimately this could help explain geographic differences in heart disease and many other chronic diseases linked to sleep medicine. More research is needed to better understand this complex relationship.

Health care disparities have also impacted sleep apnea diagnosis; data suggest that African American and rural patients are less likely to get diagnosed with sleep apnea.[11,31] Geospatial mapping can assist in recognizing vulnerable populations and help reduce this gap.

Our study has several strengths and weaknesses that should be noted. This study was conducted using data from a well-structured hospital sleep medicine program affiliated with a large regional health care system. As such, we were able to collect data from all potential individuals referred to the sleep medicine program. However, residual bias due to undocumented and undiagnosed medical conditions can occur from coding discrepancies and errors that are inherent in the use of administrative claims data.[34] Additionally, GWLR is subject to issues with multicollinearity and kernel bandwidth selection.[35] Some patients may also have elected to get care locally outside our health care system. We do not believe this would be a significant number because West Virginia University has the most expansive health care network in the state. The study also did

Figure 4—Relationship between predicted probability of sleep adherence and distance.



not analyze the impact of comorbid conditions, which may also affect no-show rates. Finally, this study is exploratory in nature and further studies are required to examine the effects of individual factors, community-level factors, and built environment on adherence to sleep study.

CONCLUSIONS

Our study aimed to determine factors leading to high no-show rate at a sleep center postdischarge using geospatial data and suggests that among individual factors health literacy may be more significant than age, sex, and BMI. Among community factors, distance to a sleep center also influences adherence, but not DCI or rurality. Certain zip codes appear to be high risk for poor adherence and investigations are needed to examine this further. Interventions and resources targeted at alleviating health literacy may improve adherence with follow up in high-risk regions. Community-level disparities do play a role to a lesser level and may also explain some geographic differences.

ABBREVIATIONS

BMI, body mass index
DCI, Distressed Communities Index
GWLR, geographically weighted logistic regression
PSG, polysomnography

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SUBMISSION & CORRESPONDENCE INFORMATION

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DISCLOSURE STATEMENT

All authors have seen and approved the manuscript. Work for this study was performed at West Virginia University, Morgantown, West Virginia. S.S. is on the speakers bureau of Zoll Respicardia Inc. and has received research grants from Zoll Respicardia Inc. and INARI Inc. The other authors report no conflicts of interest.