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Synergistic effects of social determinants of health and race-ethnicity on 30-day all-cause readmission disparities: a retrospective cohort study

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ABSTRACT

Objective The objective of this study is to assess the effects of social determinants of health (SDOH) and race-ethnicity on readmission and to investigate the potential for geospatial clustering of patients with a greater burden of SDOH that could lead to a higher risk of readmission.

Design A retrospective study of inpatients at five hospitals within Henry Ford Health (HFH) in Detroit, Michigan from November 2015 to December 2018 was conducted.

Setting This study used an adult inpatient registry created based on HFH electronic health record data as the data source. A subset of the data elements in the registry was collected for data analyses that included readmission index, race-ethnicity, six SDOH variables and demographics and clinical-related variables.

Participants The cohort was composed of 248 810 admission patient encounters with 156 353 unique adult patients between the study time period. Encounters were excluded if they did not qualify as an index admission for all payors based on the Centers for Medicare and Medicaid Service definition.

Main outcome measure The primary outcome was 30-day all-cause readmission. This binary index was identified based on HFH internal data supplemented by external validated readmission data from the Michigan Health Information Network.

Results Race-ethnicity and all SDOH were significantly associated with readmission. The effect of depression on readmission was dependent on race-ethnicity, with Hispanic patients having the strongest effect in comparison to either African Americans or non-Hispanic whites. Spatial analysis identified ZIP codes in the City of Detroit, Michigan, as over-represented for individuals with multiple SDOH.

Conclusions There is a complex relationship between SDOH and race-ethnicity that must be taken into consideration when providing healthcare services. Insights from this study, which pinpoint the most vulnerable patients, could be leveraged to further improve existing models to predict risk of 30-day readmission for individuals in future work.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ Multivariable logistic regression models fit using generalised estimating equations (GEE) were applied to examine the combined effects of social determinants of health (SDOH) and race-ethnicity on readmission.

⇒ Spatial analyses were conducted to determine the geographical clustering of individuals with multiple SDOH.

⇒ The combined use of multivariable GEE models and spatial analyses enabled a comprehensive investigation that included evaluating key SDOH-related variables associated with readmission and investigating geospatial clustering of patients with a greater burden of SDOH; future work will explore how these factors can be integrated with other characteristics to enhance existing readmission risk prediction models, such as using LACE index (length of stay, acuity of admission, comorbidity index and emergency room visit in the past six months) for predicting readmissions.

⇒ The data source used in this study is limited to one health system; however, this system consists of five hospital facilities and serves a socioeconomically and racially diverse population throughout the Metropolitan Detroit and Jackson area.

INTRODUCTION

Hospital readmissions are common and a topic of great concern given their implications for the quality of healthcare and readmission cost burden.[1 2] For example, in 2018, the Nationwide Readmission Database showed an all-payer readmission rate of 14% (per 100 index admissions) and an average readmission cost of US$15 200 for 30-day all-cause adult hospital readmissions.[3] Hospital readmission rates have been used by the Centers for Medicare & Medicaid Service (CMS) as a public reporting quality metric to determine hospital reimbursements or penalties

for excess risk-standardised readmissions.[4] Reduction in hospital readmission rates has been a priority for the improvement of healthcare quality and patient clinical outcomes. In addition to the demographic and clinical characteristics of patients including medical, procedural and operational factors, there is evidence that both race-ethnicity and social determinants of health (SDOH) are important factors associated with readmission.[5–7] SDOH encompass social, economic and environmental conditions that affect the health of people and communities.[8]

The effects of race-ethnicity and SDOH on hospital readmissions have been explored within the settings of both Medicare and surgical/disease-related cohorts.[6 7 9–11] Previous results have shown that African Americans had a higher risk of readmission than non-Hispanic white patients within 30 days following some surgical procedures.[9 12–15] Regarding the relationship between SDOH and readmission, the Area Deprivation Index (ADI)[7]—a composite measure used to assess socioeconomic status at the census-block level—is known to significantly affect outcomes related to health quality. Patients living in a more deprived communities (higher ADI scores) were more likely to be readmitted, particularly those with Medicare fee-for-service insurance, those who underwent surgical procedures, or those who suffered from sepsis.[6 16–18] These findings indicate that neighborhood-level factors, along with individual-level SDOH, should be taken into account when evaluating the impact of social factors on quality metrics.[19]

Although there is growing evidence of a strong association between SDOH or race-ethnicity and hospital readmission, limited research exists on their joint effects in broader population settings, as well as on identifying spatial clusters of readmission risk linked to individuals with lower socioeconomic status. This study aims to fill these gaps by examining the synergistic effects of SDOH and race-ethnicity on readmission across the entire adult inpatient population and investigating the potential for geospatial clustering of patients who have a greater burden of SDOH that could lead to a higher risk of readmission.

METHODS

Data sources and study design

After receiving approval from the Henry Ford Health (HFH) institutional review board (Protocol #12184), this observational retrospective study was conducted using electronic health record (EHR) data from HFH in Detroit, Michigan, a large integrated and comprehensive care system that services a racially and socioeconomically diverse population in southeastern and southcentral Michigan, which includes the City of Detroit. To study 30-day all-cause readmission, this study used a subset of the data elements extracted from the EHR in an HFH adult inpatient registry including race-ethnicity, SDOH and other covariates including age, gender, Charlson comorbidities and primary diagnosis categories.[14] The cohort was composed of 248 810 admission patient encounters between November 2015 and December 2018 for 156 353 unique patients that were 18 years or older. Encounters were excluded from the study if they did not qualify as an index admission for all payors based on the CMS definition that the patients had following discharge dispositions including short-term hospital, expired, another healthcare facility, left against medical advice and expired in a medical facility.

Key variable definitions

Primary outcome: the primary outcome used was 30-day all-cause readmission. This binary, admission-level variable was primarily based on internal readmissions identified in the HFH EHR system. Internal readmissions were supplemented by external readmission data from the Michigan Health Information Network (MiHIN). Post-acute referral information was also used to validate the external admissions identified by MiHIN.

Race-ethnicity: according to our study population and purpose, a new categorical race-ethnicity variable was constructed as four groups based on a patient's self-reported race and ethnicity: African American, Hispanic, non-Hispanic white and other.[20] African Americans include any patient who identified their race as black or black/other. Hispanics consist of all non-African American patients who reported their race or ethnicity as Hispanic or Latino. Non-Hispanic white individuals include patients who identified their race as white and their ethnicity as non-Hispanic. Lastly, other patients include those who do not fall into the first three groups and those who did not report (or declined to report) their race or ethnicity.

SDOH: our key independent variables were six commonly accessible SDOH: drug use, lives alone, depression history, dual eligible (eligible for both Medicare and Medicaid), insurance type and ADI. The first three SDOH are all binary variables obtained from the flowsheet data in the HFH EHR system. Insurance type was collected from billing records, where dual eligible is a binary flag. ADI is a measure of neighbourhood socioeconomic disadvantage based on four factors: unemployment, poverty, education and housing quality.[7 21] This study used ADI data generated at the University of Wisconsin-Madison School of Medicine and Public Health and includes 2015 ADI national percentile rankings[22] for 8160 different census block groups in Michigan. Based on our inpatient registry, each patient's street address at the time of initial admission was mapped to ZIP+4 codes using ArcGIS software and then linked to the ADI dataset at the census block group level. A higher ADI score implies greater area deprivation. Due to the skewed nature of the ADI national scores in the Metropolitan Detroit area, an ordinal ADI variable with four groups based on the ADI quartiles for the study sample was created. Treating ADI as both continuous and ordinal categorical variables allowed for the exploration of linear and non-linear deprivation effects on readmission.

Comorbidities and primary diagnoses: in addition to age and gender, two other potential key confounding variables included were Charlson comorbidities and Agency for Health Care Research and Quality (AHRQ) ICD-10-CM Diagnosis Code and Clinical Classifications Software Refined (CCSR) Categories for primary diagnosis.[23] These variables were also reported based on the HFH EHR system data for each initial admission. Using a look-back period of 1 year from the admission date for each patient encounter, Charlson Comorbidity Index (CCI), a weighted index of 17 comorbid conditions, was calculated based on these patients' diagnosis records.[8 24] Details on methods for the CCI calculations were described in the literatures.[25 26] For the AHRQ CCSR categories, the top 15 most frequent primary diagnosis categories were included as binary flags after the preliminary analysis.

Statistical analysis methods

A descriptive analysis was conducted that reported frequency count and percentages for categorical variables (gender, race-ethnicity, ADI quartiles, drug use, lives alone, depression, dual eligible, insurance type, 17 individual chronic condition indicators and top 15 most frequent primary diagnosis categories) and means and SD for continuous variables (age at admission, ADI national rank and CCI) overall and by 30-day readmission status. Further, univariable and multivariable logistic regression models, fit using generalised estimating equations (GEE), were applied to test whether SDOH and race-ethnicity were associated with readmission. The common set of potential confounders included in each adjusted model were age, gender, individual Charlson-related comorbidities and AHRQ CCSR for primary diagnosis categories. The multivariable GEE included all SDOH variables, race-ethnicity and these covariates. The GEE model was employed to account for the within-subject correlation induced by the inclusion of multiple admission by the same subject.[27] The encounters with missing data (0.4% of encounters) were removed from the analysis.

Also, to determine whether the effects of SDOH were dependent on race-ethnicity, the quasi-likelihood ratio test[28 29] was conducted to test the difference between two multivariable GEE models with and without multiplicative SDOH-by-race-ethnicity interaction terms (based model vs models with each interaction term). For significant interactions indicating race-ethnicity specific SDOH effect, multivariable GEE models for non-Hispanic white, African American, Hispanic and other were then estimated to assess SDOH effects within each specific population.

Additionally, a multivariable GEE model was constructed, using all significantly associated variables including SDOH, race-ethnicity and their multiplicative interactions. From this model, each individual's quantified value (ie, natural logarithm of their odds of readmission) was calculated and used as an encounter-level risk score. The patient encounter-level scores were then connected to the individual patient's residential ZIP code to calculate ZIP code-level readmission scores that were subsequently used to determine geospatial clusters by applying spatial autocorrelation analysis.[30] To account for multiple encounters (admissions) for a single patient, the encounter-level risk scores were aggregated into the patient-level scores by calculating their median values from the scores with the most frequent ZIP code location among their residential addresses. The ZIP code-level scores were then generated based on median patient-level scores mapping to each ZIP code within the three main counties served by HFH—Wayne, Oakland and Macomb in Michigan. To identify geospatial clustering, Local Moran's I statistics[31 32] were then calculated (with the neighbourhood structure defined by a Gabriel network) for the ZIP code-level risk scores. A significant and positive value for local Moran's I implies that a ZIP code has a risk score similar to (ie, spatially autocorrelated) its neighbouring ZIP codes. A significant and negative local Moran's I implies that a ZIP code is dissimilar to its neighbours. These values were considered significant if the corresponding false discovery rate (FDR)-adjusted p value was less than 0.05.[33–35] All analyses described above were performed in R V.3.6.2.[36] The overview and workflow of the methods including the key components and processes are described in online supplemental figure S1.

Patient and public involvement

None.

RESULTS

Descriptive characteristics of inpatient cohort

From a total of 248 810 patient encounters (156 353 patients), there were 34 901 readmissions (14%) (table 1). Of these admissions, 62.9% of the patients were non-Hispanic whites; 26.9% were African Americans; and 3.2% were Hispanics. The remaining 7.0% of patients identified as another race-ethnicity or did not have this information recorded. The average patient age was 60 years old, and women made up 58.1% of the cohort. In this study, 96.1% of patient addresses were successfully matched to their corresponding census block group, and these individuals lived in neighbourhoods with a median ADI national percentile ranking of 69, which is well above the national median ADI of 50.[7] Of these patients, 5.3% have a history of drug use; 18.0% live alone; 12.8% have been diagnosed with depression; 12.1% are dual eligible; 54.4% have Medicare insurance; and 18.8% have Medicaid insurance. According to the prevalence of primary diagnoses and comorbidities in the cohort (table 1), the most common primary diagnosis among these encounters was septicaemia (7.1%), while the most common comorbidity was chronic obstructive pulmonary disease (33.2%). Other common comorbidities include diabetes without chronic complications (31.4%), renal disease (26.5%) and congestive heart failure (25.6%).

Regarding the SDOH and race-ethnicity variables, patients within the 30-day readmission group had higher

Table 1 Characteristics of patient encounters by 30-day readmission status

	Total (n=248 810)	Not readmitted (n=213 909)	Readmitted (n=34 901)
Demographics			
Age, mean (SD)	59.8 (±19.7)	59.1 (±20.1)	64.5 (±16.9)
Gender—female, n (%)	144 671 (58.1)	126 482 (59.1)	18 189 (52.1)
Race-ethnicity, n (%)			
Non-Hispanic white	156 589 (62.9)	135 055 (63.1)	21 534 (61.7)
African American	67 008 (26.9)	56 373 (26.4)	10 635 (30.5)
Hispanic	7899 (3.2)	7078 (3.3)	821 (2.4)
Other	17 314 (7.0)	15 403 (7.2)	1911 (5.5)
Social determinants of health			
ADI National Rank, mean (SD)	65.4 (±26.2)	65.0 (±26.2)	67.7 (±25.8)
ADI quartiles*, n (%)			
Q1 (1–45)	61 368 (24.7)	53 772 (25.1)	7596 (21.8)
Q2 (46–69)	58 864 (23.7)	50 655 (23.7)	8209 (23.5)
Q3 (70–90)	61 378 (24.7)	52 596 (24.6)	8782 (25.2)
Q4 (91–100)	57 555 (23.1)	48 416 (22.6)	9139 (26.2)
Drug use, n (%)	13 226 (5.3)	10 739 (5.0)	2487 (7.1)
Lives alone, n (%)	44 850 (18.0)	37 037 (17.3)	7813 (22.4)
Depression, n (%)	31 821 (12.8)	26 137 (12.2)	5684 (16.3)
Dual eligible, n (%)	30 220 (12.1)	23 962 (11.2)	6258 (17.9)
Insurance, n (%)			
Commercial	63 677 (25.6)	58 148 (27.2)	5529 (15.8)
Medicaid	46 849 (18.8)	41 352 (19.3)	5497 (15.8)
Medicare	135 401 (54.4)	111 705 (52.2)	23 696 (67.9)
Other/unknown	2883 (1.2)	2704 (1.3)	179 (0.5)
Charlson comorbidities			
Charlson Comorbidity Index, mean (SD)	3.8 (2.7)	3.6 (2.6)	5.3 (2.8)
Chronic obstructive pulmonary disease, n (%)	82 591 (33.2)	67 147 (31.6)	15 444 (44.3)
Diabetes without chronic complication, n (%)	78 135 (31.4)	63 204 (29.5)	14 931 (42.8)
Renal disease, n (%)	65 976 (26.5)	50 909 (23.8)	15 067 (43.2)
Congestive heart failure, n (%)	63 633 (25.6)	49 034 (22.9)	14 599 (41.8)
Diabetes with chronic complication, n (%)	43 312 (17.4)	33 276 (15.6)	10 036 (28.8)
Myocardial infarction, n (%)	40 552 (16.3)	32 017 (15.0)	8535 (24.5)
Peripheral vascular disease, n (%)	38 145 (15.3)	29 711 (13.9)	8434 (24.2)
Malignancy without metastasis, n (%)	36 215 (14.6)	28 390 (13.3)	7825 (22.4)
Cerebrovascular disease, n (%)	36 204 (14.6)	29 479 (13.8)	6725 (19.3)
Dementia, n (%)	22 426 (9.0)	18 183 (8.5)	4243 (12.2)
Metastatic solid tumour, n (%)	13 861 (5.6)	10 353 (4.8)	3508 (10.1)
Mild liver disease, n (%)	11 639 (4.7)	8472 (4.0)	3167 (9.1)
Peptic ulcer disease, n (%)	11 828 (4.8)	9254 (4.3)	2574 (7.4)
Rheumatic disease, n (%)	9409 (3.8)	7606 (3.6)	1803 (5.2)
Hemiplegia or paraplegia, n (%)	8040 (3.2)	6577 (3.1)	1463 (4.2)
Moderate or severe liver disease, n (%)	7564 (3.0)	5230 (2.4)	2334 (6.7)
AIDS, n (%)	730 (0.3)	555 (0.3)	175 (0.5)

Continued

Table 1 Continued

	Total (n=248 810)	Not readmitted (n=213 909)	Readmitted (n=34 901)
Primary diagnoses			
Septicaemia, n (%)	17 681 (7.1)	14 602 (6.8)	3079 (8.8)
Hypertension with complications and secondary hypertension, n (%)	13 181 (5.3)	10 366 (4.8)	2815 (8.1)
Osteoarthritis, n (%)	10 385 (4.2)	9972 (4.7)	413 (1.2)
Spondylopathies/spondyloarthropathy (including infective), n (%)	6724 (2.7)	6269 (2.9)	455 (1.3)
Acute myocardial infarction, n (%)	6150 (2.5)	5249 (2.5)	901 (2.6)
Respiratory failure; insufficiency; arrest, n (%)	5600 (2.3)	4366 (2.0)	1234 (3.5)
Cardiac dysrhythmias, n (%)	5469 (2.2)	4717 (2.2)	752 (2.2)
Chronic obstructive pulmonary disease and bronchiectasis, n (%)	5114 (2.1)	4047 (1.9)	1067 (3.1)
Cerebral infarction, n (%)	5018 (2.0)	4486 (2.1)	532 (1.5)
Acute and unspecified renal failure, n (%)	4748 (1.9)	3831 (1.8)	917 (2.6)
Diabetes mellitus with complication, n (%)	4404 (1.8)	3588 (1.7)	816 (2.3)
Skin and subcutaneous tissue infections, n (%)	4012 (1.6)	3557 (1.7)	455 (1.3)
Pneumonia (except that caused by tuberculosis), n (%)	3783 (1.5)	3237 (1.5)	546 (1.6)
Urinary tract infections, n (%)	3642 (1.5)	3109 (1.5)	533 (1.5)
Gastrointestinal haemorrhage, n (%)	3524 (1.4)	2879 (1.3)	645 (1.8)

*ADI quartiles: the quarters were assigned based on 96.1% of total patient encounters where the living addresses were successfully mapped to the corresponding census block group.
ADI, Area Deprivation Index; n(%), count and column percent.

percentages of African American patients (30.5% vs 26.4%), Medicare coverage (67.9% vs 52.2%), and lived in more deprived areas in general (mean ADI ranking score 67.7 vs 65) compared with those who did not readmit within 30 days (table 1). Also, these individuals in the readmission group had higher proportions of drug use, lives alone, depression, dual eligible and living in the most deprived areas, Q4 (ie, >75th ADI percentile) (table 1).

Effects of SDOH and race-ethnicity on readmission

Based on the univariable models, all SDOH and race-ethnicity were associated with the risk of 30-day readmissions (table 2). These variables remained independently associated with readmission in the multivariable logistic GEE model (table 2). In the multivariable model, the largest effects were for drug use (OR 1.35; 95% CI 1.26 to 1.46). The patients who were covered by Medicaid or Medicare insurance had higher odds of readmission in comparison with those with any commercial insurance (OR for Medicaid vs Commercial, 1.28; 95% CI 1.21 to 1.36; OR for Medicare vs Commercial, 1.26; 95% CI 1.19 to 1.33). Furthermore, for each 10-unit increase on ADI, the odds of readmission increased by 1.02. Finally, African American patients were more likely to be readmitted in comparison to non-Hispanic white patients (OR, 1.08; 95% CI 1.04 to 1.13). In contrast, Hispanic patients were less likely to be readmitted (OR, 0.82; 95% CI 0.73 to 0.91) in comparison to non-Hispanic white patients. The p values, as determined by the univariable and multivariable GEE models, are shown in online supplemental table S1.

Race-ethnicity specific effects of SDOH on readmission

To assess whether SDOH effects differed based on race-ethnicity, race-ethnicity-by-SDOH multiplicative interaction terms were introduced one at a time into the multi-SDOH GEE model. The results of quasi-likelihood ratio test of interaction showed that both the effects of depression (omnibus interaction p=0.002) and the effect of insurance (omnibus interaction p<0.001) on readmission were dependent on race-ethnicity. From the GEE models with interaction terms, it showed that Hispanic patients had different effects of depression (interaction term p=0.026) and Medicaid insurance versus all other insurance types (interaction term p=0.021) on 30-day readmission in comparison to non-Hispanic white patients. To further characterise these race-ethnicity specific effects, the readmission model was stratified to produce African American, non-Hispanic white, Hispanic and other specific effects (table 3). The p values obtained from the multivariable GEE models

Table 2 Univariable and multivariable ORs for 30-day readmission from GEE models

	Univariable GEE (unadjusted)		Univariable GEE (adjusted*)		Multivariable GEE (adjusted*)	
	OR	95% CI	OR	95% CI	OR	95% CI
Race-ethnicity	Reference: non-Hispanic white					
African American	1.21	1.16 to 1.26	1.18	1.14 to 1.23	1.08	1.04 to 1.13
Hispanic	0.70	0.62 to 0.78	0.86	0.78 to 0.96	0.82	0.73 to 0.91
Other	0.77	0.72 to 0.78	0.90	0.85 to 0.96	0.90	0.84 to 0.96
ADI (continuous)††	1.04	1.04 to 1.05	1.04	1.03 to 1.04	1.02	1.01 to 1.02
Drug use	1.48	1.37 to 1.59	1.54	1.43 to 1.65	1.35	1.26 to 1.46
Lives alone	1.42	1.36 to 1.47	1.17	1.13 to 1.22	1.11	1.07 to 1.16
Depression	1.43	1.36 to 1.50	1.25	1.30 to 1.31	1.21	1.16 to 1.27
Dual eligible	1.82	1.73 to 1.90	1.37	1.31 to 1.43	1.25	1.19 to 1.31
Insurance	Reference: commercial					
Medicaid	1.42	1.34 to 1.51	1.36	1.28 to 1.44	1.28	1.21 to 1.36
Medicare	2.44	2.34 to 2.54	1.45	1.37 to 1.53	1.26	1.19 to 1.33
Other/unknown	0.71	0.59 to 0.86	0.77	0.64 to 0.92	0.83	0.69 to 0.99

*GEE models adjusted for age, gender, individual Charlson-related comorbidities, and Agency for Health Care Research and Quality Clinical Classifications Software Refined for primary diagnosis categories.
†OR for 10-unit increase in ADI.
ADI, Area Deprivation Index; GEE, generalised estimating equations.

are presented in online supplemental table S2. For depression, the stratified analyses demonstrated that while depression was associated with an increased risk of readmission in all four race-ethnicity groups, the largest effect of depression on readmission was observed for Hispanic patients (OR, 1.51; 95% CI 1.12 to 2.02), and consistent with the test of interaction, this effect was most disparate with that among non-Hispanic white patients (OR, 1.18; 95% CI 1.12 to 1.24). For Medicaid insurance, within each race-ethnicity subgroup, both African American and non-Hispanic white patients who were covered by Medicaid insurance had a higher risk of readmission compared with those with commercial insurance (table 3), with non-Hispanic white patients having the highest risk (OR, 1.32; 95% CI 1.21 to 1.43). In contrast, there were no significant effects for Hispanic and other race-ethnicity groups, and consistent with the interaction test, Hispanic patients had the most disparate effect

Table 3 Multivariable ORs for 30-day readmission from GEE models by race-ethnicity

	Multivariable GEE* (adjusted and without interactions)							
	African American		Non-Hispanic white		Hispanic		Other	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
ADI (continuous)††	1.02	1.00 to 1.03	1.01	1.01 to 1.02	1.06	1.00 to 1.12	1.03	1.00 to 1.05
Drug use	1.35	1.21 to 1.50	1.32	1.19 to 1.46	1.62	1.06 to 2.45	1.38	0.95 to 2.02
Lives alone	1.10	1.02 to 1.18	1.12	1.06 to 1.17	1.20	0.91 to 1.59	1.08	0.89 to 1.29
Depression	1.22	1.12 to 1.35	1.18	1.11 to 1.24	1.51	1.12 to 2.02	1.46	1.18 to 1.81
Dual eligible	1.25	1.16 to 1.36	1.24	1.15 to 1.32	1.14	0.85 to 1.52	1.29	1.07 to 1.56
Insurance	Reference: commercial							
Medicaid	1.29	1.17 to 1.43	1.32	1.21 to 1.43	0.95	0.72 to 1.26	1.06	0.86 to 1.31
Medicare	1.22	1.10 to 1.37	1.31	1.22 to 1.41	0.92	0.62 to 1.35	1.02	0.81 to 1.28
Other/unknown	0.63	0.44 to 0.89	0.93	0.74 to 1.18	0.58	0.29 to 1.19	1.01	0.49 to 2.09

*For each race-ethnicity group, multivariable GEE model adjusted for age, gender, individual Charlson-related comorbidities, and AHRQ CCSR for primary diagnosis categories.
†OR for 10-unit increase in ADI.
ADI, Area Deprivation Index; GEE, generalised estimating equations.

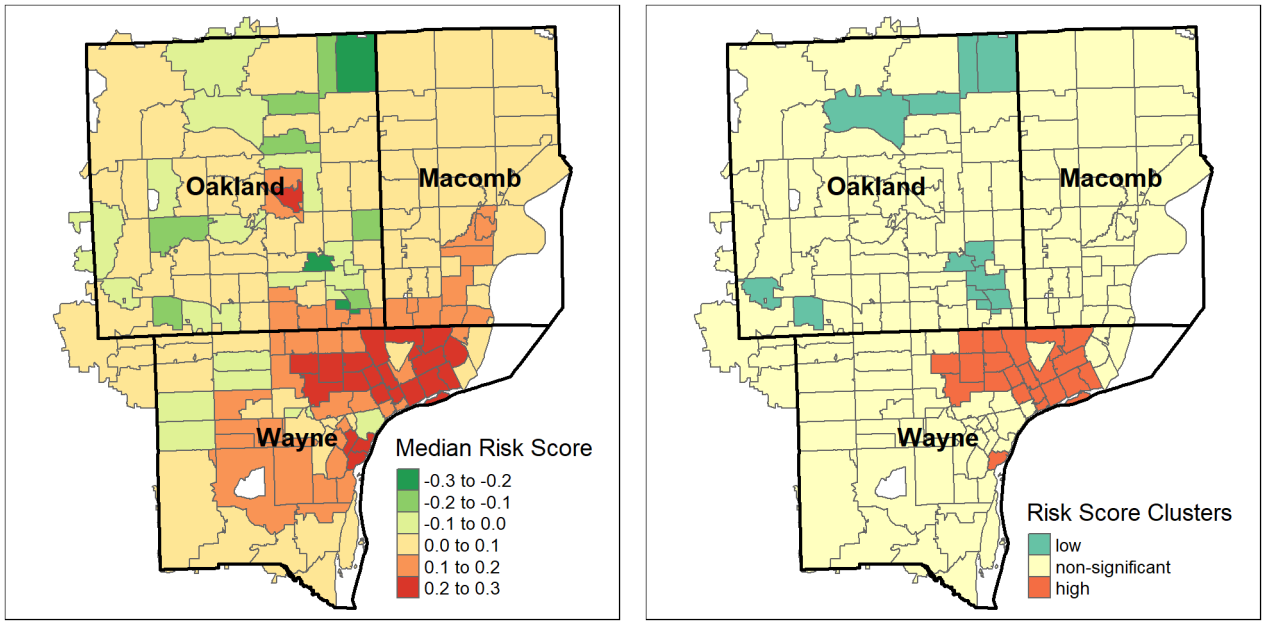

Figure 1 Median risk score and clusters by ZIP code.

(OR, 0.95; 95% CI 0.72 to 1.26) in comparison to non-Hispanic white patients.

Risk score for spatial analysis

After assigning model-based readmission risk scores to all patients, the median risk score for each ZIP code in the tricounty area was calculated, which covered the majority (83.4%) of the patient encounters in the study. Two significant clusters of high-risk scores based on Moran's I values (FDR-adjusted p<0.05) were detected in the cities of Detroit and Ecorse (figure 1). These clusters covered 21 ZIP codes, all of which showed high-risk scores. It should be noted that these ZIP codes with similar median risk scores could vary in their proportions of high-level risk scores due to various distributions of individual patient scores within each ZIP.

Although similar risk scores appear within these hotspots, there is heterogeneity in race-ethnicity and the SDOH contributing to scores in each ZIP code. Figure 2 shows the distribution of race-ethnicity for the tricounty area, and figure 3 displays the proportions of each SDOH by quintiles. Based on these maps, it was found that nearly the entire hotspots fell in the highest 20% for ADI, drug use, Medicaid insurance and dual eligibility. Also, the majority of the patients living in the hotspots

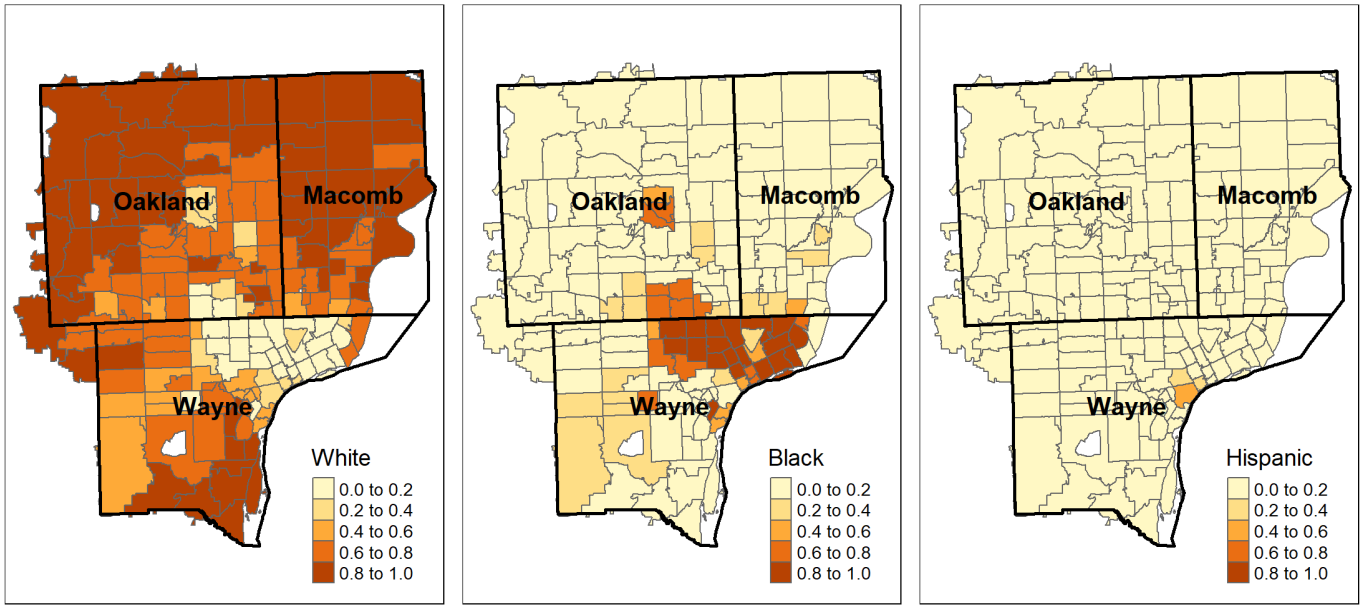

Figure 2 Proportion of race-ethnicity by ZIP code.

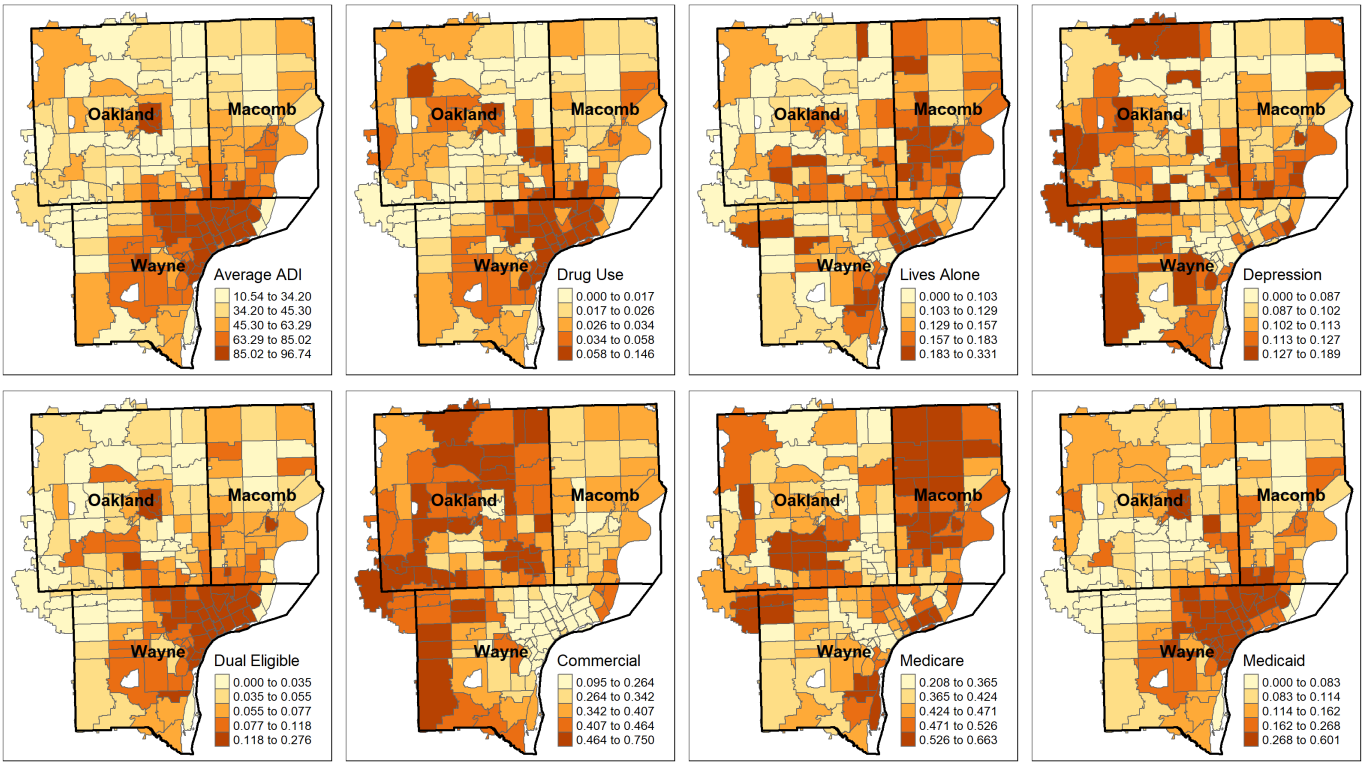

Figure 3 Proportion of SDOH by ZIP code. ADI, Area Deprivation Index; SDH, social determinants of health.

were African Americans. Additionally, there was a high proportion of living alone within the Detroit hotspot, the Corktown, Midtown, Downtown, North End, New Center and Jefferson Corridor neighbourhood areas. The rate of diagnosed depression history also varied greatly throughout this area.

DISCUSSION

The study demonstrated that living in more severely disadvantaged neighbourhoods (higher ADI) and other SDOH (drug use, lives alone, depression history, dual eligible and insurance type) increased the risk for hospital readmission in patients overall. This finding is consistent with other studies demonstrating that both community-level and patient-level circumstances can influence readmission.[6 37] A lack of community resources—such as public transportation, grocery stores, pharmacies and a generally impoverished environment—could increase the difficulty of postdischarge health management that leads to an increased risk of readmission.[38] Therefore, our finding suggested that SDOH measures should be considered as one of the indicators used for screening 30-day readmission risk during hospitalisation.

Additionally, the synergistic effects of SDOH and race-ethnicity on readmission were investigated through multivariable regression models. The results revealed different groups of individuals at high risk of readmission that were not defined by a single predictor alone. While all SDOH were independently and significantly associated with an increased risk of readmission, the effect of depression was highest for Hispanic patients. According to previous studies, Hispanic patients with depression had an increased risk of adverse health outcomes,[39] which could impact readmission. Focusing on depression care in this population could potentially be a way to reduce readmission rates among these patients. In addition, from the perspective of geospatial information, the varied depression diagnosis rates mapping across geographical space in the tricounty area indicate a need for mental health support for inpatient individuals coming from high risk of readmission ZIP codes. Regarding the effect of Medicaid insurance coverage across different race-ethnicity subgroups, a previous study found Hispanics were associated with lower risk of readmissions than whites,[40] which is consistent with our finding. While these race-ethnicity-by-SDOH interactions were significant, it is acknowledged that race-ethnicity is a complex construct and that components of those constructs are driving these findings, which could also vary differ across different health systems. Additional studies should be conducted to identify the root causes of these race-ethnicity specific effects, which could further aid in the precision targeting of services to reduce the likelihood of readmission.

For the spatial autocorrelation analyses, the results identified the City of Detroit (Wayne County, Michigan) as being over-represented for the group of individuals with higher median risk scores indicating a higher burden of SDOH and a higher proportion in African Americans.[7] In comparison with the other residents in Michigan, people living in the City of Detroit had a higher burden of SDOH

including lower percentile of income, education level and health insurance coverage (year 2014–2018).[41] Also, Rivera's study indicates that African American patients compared with white, or Medicaid-eligible patients, were less likely to have activated their patient online portal ('MyChart') for telehealth.[42] Providing additional education and training to support the use of clinical telehealth technologies, especially for people in Detroit, could help reduce unplanned readmissions[43] and improve a patient's health trajectory.[44]

The study results, which reveal a complex interaction between SDOH and race-ethnicity impacting 30-day readmission rates, support the growing number of evidence that social factors should be considered in the Hospital Readmissions Reduction Program (HRRP).[45] As a value-based payment model of CMS, HRRP determines financial penalties for hospitals by comparing actual to expected risk-standardised 30-day readmission rates.[46] The base model initially adjusted for patient age, sex and comorbidities, but was subsequently expanded to account for social risk factors after CMS recognised the importance of such adjustments.[45 47] This modification seeks to promote equity in payment models, protecting hospitals from penalties simply for serving a high number of socially vulnerable patients. As debates continue over the appropriate methods of social risk adjustment in such models,[45] our study offers potential insights for refining HRRP's approach by considering the patient-level and community-level SDOH as well as its interactions with race-ethnicity.

In this study, the variables used in this study to construct the multivariable GEE models are available in most EHR systems, including SDOH, race-ethnicity and covariates variables (eg, patient demographics, Charlson-related comorbidities, and AHRQ CCSR primary diagnosis categories). As underlying risk groups are likely to be unique for different healthcare systems, these key features and the methods used in this study could be applied to identify the high risk for readmission patients in different healthcare systems. Our findings suggest that integrating model results with geospatial analyses could help identify the most vulnerable patients. The next critical step is to assess the effectiveness of the retrospective models in predicting prospective readmissions at HFH. This will involve further understanding of how SDOH factors can be incorporated with other characteristics to enhance existing readmission risk prediction models, such as those used in the LACE index.[48 49] If proven proactively effective in future studies, this approach could become a valuable screening tool for developing intervention plans, for example, improving education and postdischarge support for targeted patients. Additionally, an effective discharge patient education and follow-up care with a multidisciplinary team involvement[50]—including medical providers, case managers, patient education units, social workers and patient representatives—is crucial, as it significantly improves clinical outcomes and decrease readmission rates.[51–55] Future research for the effects of targeted interventions on hospital readmissions is necessary before this strategic framework can be implemented. Once validated, the approach will be used to tailor education programmes to individuals based on their patient-level profiles, considering SDOH, residential locations and other key factors. This may also enable clinical teams to offer follow-up referrals for those high-risk patients to support their postdischarge needs.[43 56]

This study has limitations that should be noted. The data source used (ie, an adult inpatient registry) is limited to one health system. However, this system consists of five hospital facilities and serves a socioeconomically and racially diverse population throughout the Metropolitan Detroit and Jackson area, which is home to approximately 80% of the approximately 10 million people living in the state of Michigan. Additionally, the 2015 ADI data used in this study were constructed based on the American Community Survey 5-year data, representing the limited time from 2011 to 2015.[22] Gathering neighborhood-level data, such as the ADI, is more challenging than collecting individual-level SDOH through direct patient surveys, particularly since converting patients' living addresses to their corresponding census block groups can be complicated due to address typos. In this study, the ADI was obtained for 96.1% of total patient encounters, where their living addresses were successfully mapped to the corresponding census block group. Furthermore, the true 30-day readmission rate of these patient populations is likely underestimated, as patients could be readmitted to a hospital outside of HFH. To mitigate the effects of this limitation in this inpatient registry, supplementary admission data were collected from MiHIN and postacute referral information. Some additional readmission cases were not captured, such as those where patients that occurred in HFH was a readmission to a prior hospitalisation at an outside hospital. However, HFH is not monetarily penalised for these cases.

CONCLUSIONS

Findings from this study demonstrate the complex interplay between SDOH and race-ethnicity influencing 30-day readmission. Integrating model results with geospatial analyses could identify the most vulnerable patients. Future studies will build on insights from this study incorporate additional SDOH-related variables (eg, income, alcohol use, tobacco habits, etc), as well as clinical, and discharge features, to improve existing predictive models for 30-day readmission.

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