ORIGINAL RESEARCH

Area Deprivation Index and Cardiac Readmissions: Evaluating Risk-Prediction in an Electronic Health Record

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BACKGROUND: Assessment of the social determinants of post-hospital cardiac care is needed. We examined the association and predictive ability of neighborhood-level determinants (area deprivation index, ADI), readmission risk, and mortality for heart failure, myocardial ischemia, and atrial fibrillation.

METHODS AND RESULTS: Using a retrospective (January 1, 2011–December 31, 2018) analysis of a large healthcare system, we assess the predictive ability of ADI on 30-day and 1-year readmission and mortality following hospitalization. Cox proportional hazards models analyzed time-to-event. Log rank analyses determined survival. C-statistic and net reclassification index determined the model's discriminative power. Covariates included age, sex, race, comorbidity, number of medications, length of stay, and insurance. The cohort (n=27 694) had a median follow-up of 46.5 months. There were 14 469 (52.2%) men and 25 219 White (91.1%) patients. Patients in the highest ADI quintile (versus lowest) were more likely to be admitted within 1 year of index heart failure admission (hazard ratio [HR], 1.25; 95% CI, 1.03–1.51). Patients with myocardial ischemia in the highest ADI quintile were twice as likely to be readmitted at 1 year (HR, 2.04; 95% CI, 1.44–2.91]). Patients with atrial fibrillation living in areas with highest ADI were less likely to be admitted within 1 year (HR, 0.79; 95% CI, 0.65–0.95). As ADI increased, risk of readmission increased, and risk reclassification was improved with ADI in the models. Patients in the highest ADI quintile were 25% more likely to die within a year (HR, 1.25 1.08–1.44).

CONCLUSIONS: Residence in socioeconomically disadvantaged communities predicts rehospitalization and mortality. Measuring neighborhood deprivation can identify individuals at risk following cardiac hospitalization.

Key Words: electronic health record ■ readmissions ■ risk prediction ■ social determinants of health

In 2010, the United States Department of Health and Human Services issued the Healthy People 2020 report in which social determinants of health (SDOH) were the focus.[1] The report aimed to galvanize stakeholders to address preventable barriers to healthy lives across the population. One upshot has been increased attention to SDOH as researchers and clinicians strive to better understand mechanisms of disparate healthcare outcomes. For example, low socioeconomic status (SES) has been associated with inadequate preventive health care, limited specialty care,

and poorer long-term clinical outcomes.[2–6] Decreased SES affects both acute and chronic illnesses. Poverty and low-income have been associated with increased likelihood of 30-day readmission and 5-year mortality in individuals with heart failure (HF), myocardial infarction/ischemia, and pneumonia.[2–4] Given their demonstrated relevance, the National Academy of Medicine has called for the consideration of SDOH in working toward high value care within health systems.[7]

Healthcare organizations have yet to fully incorporate the requisite tools that would enable them to map social

Nonstandard Abbreviations and Acronyms

ADI	area deprivation index
IDI	integrated discrimination index
MI	myocardial ischemia
NRI	net reclassification index
SDOH	social determinants of health
UPMC	University of Pittsburgh Medical Center

factors to health outcomes. The delayed uptake of the Healthy People 2020 goals is partly attributable to difficulty in operationalizing such initiatives into the medical record. Many health systems have begun using their own data for quality improvement initiatives, but SDOH remain underappreciated. SDOH predictors of readmission for hospitalized patients are not uniformly assessed as part of routine hospital practice or interventions. Examples of successfully ascertaining social determinants at large healthcare systems are limited[8,9] and often rely on patients to admit to predetermined screening questions.[10] Whether such integration can have a meaningful contribution to patient care remains an unresolved question.[8] SDOH are undoubtedly associated with adverse health outcomes, but leveraging available data to determine the impact of social factors has had inadequate study. For practical implementation, quantification of the effects of social factors on health would be facilitated by a single index which consolidates multiple domains into an individual measure. The resulting assessment would enable health systems to better address patients at risk for poor outcomes and groups who would benefit from targeted interventions.

The area deprivation index (ADI) incorporates relevant socioeconomic variables to provide standardized neighborhood rankings by status, thus enabling the evaluation of outcomes by geographic location based on level of disadvantage.[11] ADI quantifies 17 indicators of material and social conditions, including income, education level, employment status, and housing security. ADI is a validated marker of neighborhood disadvantage; residence within a community with high ADI is a predictor of an individual's risk for poor health outcomes.[12–14] Our objective was to examine the association between ADI and the risk of readmission and mortality within 30 days and 1 year for 3 common cardiac diagnoses for hospital admission: HF, myocardial ischemia (MI), and atrial fibrillation (AF). Our goal was to leverage our available health system data to determine a measure of SDOH that could be readily implemented to improve prediction of hospital readmission. We hypothesized that not only would ADI be associated with readmission and mortality, but also that ADI would better contribute to individual patients' risk-prediction using data from a longitudinal electronic health record (EHR) compared with data without ADI.

METHODS

Study Design

We conducted a retrospective observational analysis of an EHR database of a large regional healthcare center to demonstrate the predictive ability of neighborhood-level SDOH in determining adverse clinical outcomes. The objectives of this analysis were to assess the independent association of ADI with 30-day and 1-year readmission and mortality among individuals admitted to the hospital. In addition, we assessed the net reclassification index and integrated discrimination index for ADI to evaluate the relative contribution of neighborhood deprivation to the calibration and discrimination of risk models for hospital readmission and mortality.

Setting and Data Collection

The University of Pittsburgh Medical Center (UPMC) Health System is a large not-for-profit academic system located in the Pittsburgh, Pennsylvania region and spans across parts of Ohio, West Virginia, Maryland, and New York. Over 1 million unique patients are seen annually within UPMC, leading to ≈5.6 million outpatient encounters and 382 000 hospital admissions per year.[15] We abstracted EHR data for inpatient hospital admissions between January 1, 2011 and December 31, 2018. We collected information used to inform the study variables at index admission as well as at each readmission within our hospital system. The data that support the findings of this study are available from the corresponding author upon reasonable request.

Participants

Our cohort included individuals with an index hospitalization for 1 of 3 leading cardiac admission diagnoses: HF, MI, or AF between January 1, 2011 and December 31, 2018. Diagnoses were determined by admitting *International Classification of Diseases, Ninth and Tenth Revisions* (*ICD-9* and *ICD-10*) codes[16] as the primary admitting diagnosis. Table S1 lists relevant *ICD* codes. We included cohort participants who were at least 18 years old and were discharged alive. We excluded individuals with absence of follow-up within UPMC (ambulatory or inpatient visit) within 12 months following index admission. After index admission, we evaluated the EHR during the subsequent 12 months to identify the first readmission within 30 days or 12 months. Readmission was defined as a non-elective hospital admission via the emergency department, directly from the outpatient or residential setting, or transfer from another health system. When a patient had multiple readmissions after the index hospitalization, we used only the first readmission within either 30 days or 12 months of index discharge as the readmission. Therefore, additional readmissions beyond the first event within the time period were not counted as readmissions. A cardiac readmission was defined as one for which the primary admitting diagnosis was for either HF, MI, or AF. Death was measured by the social security death index and data available in the EHR. This analysis was approved by the University of Pittsburgh Institutional Review Board and by UPMC Quality Improvement Committee. This retrospective analysis of EHR data did not require participant informed consent.

Variables

ADI is reported as a composite score valued from 1 (least socioeconomically disadvantaged) to 100 (most socioeconomically disadvantaged) and is constructed from weighted factor score coefficients for each of its 17 indicator variables.[11,17] The ADI data set published by the University of Wisconsin is organized at the geography of ZIP+4.[17,18] We used the version of ADI updated in 2015. To match ADI to patient addresses, each patient's ZIP+4 was obtained from the public US Postal Service geocoding Application Programming Interface.[19] We grouped the ADI rankings into quintiles with the highest quintile representing the most socioeconomically disadvantaged group, as has been previously validated.[8]

Our covariates included age at time of index hospitalization as a continuous variable, binary sex category as listed in the EHR, self-reported race and Hispanic ethnicity as listed in the EHR; calculated Elixhauser comorbidity score at index admission[20]; total number of outpatient medication prescriptions listed at time of discharge from index admission, length of stay at index admission (number of days), and insurance (Medicare or Medicaid). Each of these covariates were included because of their well-documented associations with healthcare usage. The highly validated Elixhauser score is reflective of medical complexity and performs well for cardiac conditions.[21] We defined time-to-event as the time from index admission to either readmission, death, or the end of the observation period (30 days or 1 year).

Statistical Analysis

We selected the first admission within the study time frame (2011–2018) as baseline (time 0). To examine incidence rates of 30-day and 1-year readmission by hospital admission diagnosis and by ADI, we calculated the readmission rates per 1000 person-years for each of our 3 diagnoses. To estimate the incidence risk ratio, we used generalized estimating equations based on a 0-inflated Poisson model for number of readmissions of different diseases (count data). Next, we categorized ADI into quintiles for the entire cohort using a previously demonstrated and validated approach for categorizing ADI.[8]

To summarize descriptive statistics, we assessed categorical variables by frequencies and proportions and continuous variables by either mean and standard deviation or medians and interquartile ranges. We used the Kruskal–Wallis rank test for continuous variables and Chi-square test for categorical variables to compare distribution differences among groups. We used 1-way ANOVA to compare the difference of mean age across ADI quintiles.

We performed our survival analysis using Cox proportional hazards models analyzing time-to-event with multivariable adjustment. Models were censored for (1) mortality or (2) last date of contact with the UPMC healthcare system as documented by the EHR. Model 1 included age, sex, race, and ethnicity as covariates. Model 2 included variables from Model 1 with the addition of Elixhauser comorbidity score. The fully adjusted model (Model 3) included the variables from Model 2 with the addition of number of medications at discharge, length of stay at index admission, and insurance as covariates. We explored multicollinearity by examining correlation matrices and the variance inflation and tolerance in the regression analyses. We determined proportional hazards of events using the lowest ADI category as the referent. We assessed time-to-event using Kaplan–Meier and log rank analysis and plotted covariate-adjusted survival curves based on the Cox models.

To evaluate the discriminative power of the prediction models on readmission risk and mortality,

we calculated the area under the receiver operating characteristic curve based on the predicted risks determined by the logistic regression analysis using the fully adjusted model.[22] Next, we determined the C-statistic to measure the ability of the fully adjusted model to discriminate readmission from non-readmission. Because the C-statistic can be insensitive to changes in absolute risk estimates, it may not fully convey clinically meaningful results.[23] Therefore, we also assessed the contribution of ADI to the fully adjusted model by using the net reclassification index (NRI) method. NRI is a methodology to evaluate the proportion of subjects moving accurately or inaccurately from one risk category to another after adding ADI into the model. We used a category-free (continuous) NRI in this study. We additionally determined the integrated discrimination indices (IDI) using a previously validated method to further assess the predictive ability of our models.[24] Altogether, this methodology was used to provide a comprehensive calibration of our models.

Stratified and sensitivity analyses examined the effect of using ADI as a continuous variable. We also assessed mortality analyses by number of readmission events/year as a continuous variable. We evaluated potential interactions between categorical race groups (White, Black, and other [neither Black nor White]), male versus female sex, and ADI. All analyses were completed using SAS version 9.4 (SAS Institute, Cary, NC). An alpha level of 0.05 determined statistical significance.

RESULTS

Figure 1 displays the patient flow diagram. Our cohort included 27 694 individuals aged ≥18 years who were admitted to a UPMC facility between January 1, 2011 and December 31, 2018. Participants were followed for a median of 46.5 months (interquartile range, 24.4–68.1). Table 1 shows the distribution of covariates. There were 14 469 (52.2%) men and 25 219 White (91.1%) patients. Almost half (13 594, 49.1%) of cohort patients lived in neighborhoods in the 2 worst (highest) ADI quintiles. ADI quintile was significantly associated with age, sex, race, number of medications at discharge, length of stay, and insurance type.

Table 2 shows the incidence rates of 30-day and 1-year readmission by admission diagnosis and ADI quintile. Unadjusted risk estimates indicate that for each diagnosis except AF, the higher the ADI category, the higher the readmission rates. ADI was significantly associated with rates of hospitalization within 30 days of index admission for cardiac readmissions and all-cause readmissions. ADI was also associated with the 1-year readmission rates for HF, MI, AF, cardiac readmission, and all-cause readmission (P<0.001 for all). There was no significant difference in admission via emergency department versus other means (direct admission or transfer, data not shown).

Cox proportional hazards for readmission as predicted by the fully adjusted model are detailed in Table 3. The hazard ratios for Models 1 and 2 can be found in Tables S2 and S3. In the fully adjusted model for HF, patients in the highest ADI quintile had a 1-year
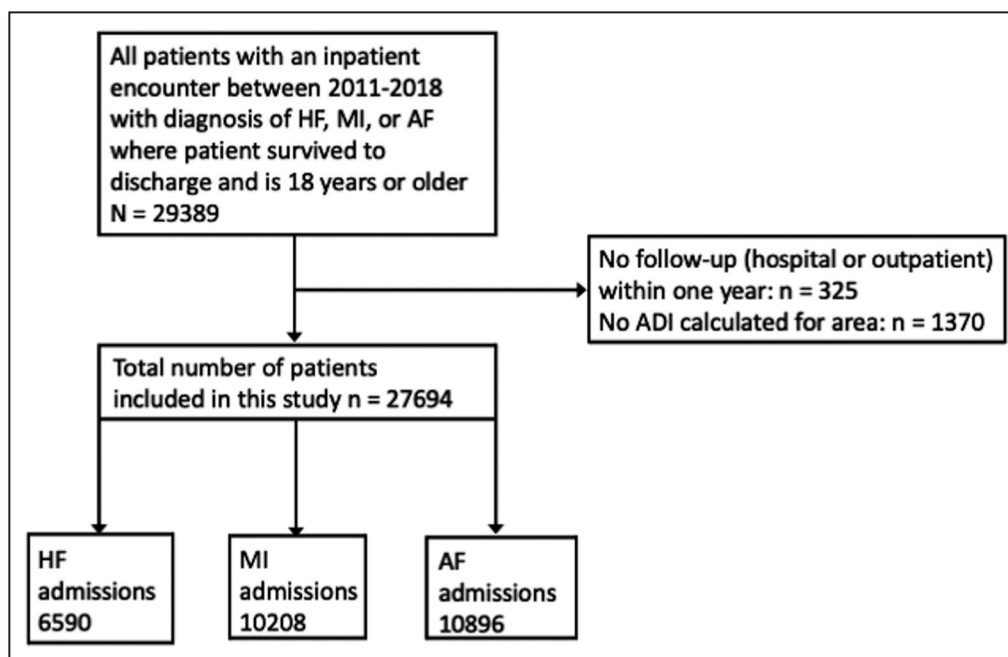

Figure 1. Participant flow sheet, criteria for selection.
ADI indicates area deprivation index; AF, atrial fibrillation; HF, heart failure; and MI, myocardial ischemia.

Table 1. Descriptive Statistics of Cohort Variables According to Quintile of Area Deprivation Index

	ADI Quintile					P Value
	1 (Least Deprived)	2	3	4	5 (Most Deprived)	
No. of patients	1877	4843	7380	8052	5542	
Age (y), mean±SD	72.4±13.3	72.1±12.8	72.0±13.1	70.7±13.4	68.2±14.1	<0.001
Male sex, n (%)	1062 (56.6)	2691 (55.6)	3950 (53.5)	4189 (52.0)	2577 (46.5)	<0.001
Race, n (%)						<0.001
White	1820 (96.9)	4708 (97.2)	7151 (96.9)	7556 (93.8)	3984 (71.9)	
Black	26 (1.4)	93 (1.9)	171 (2.3)	429 (5.3)	1503 (27.1)	
Other*	31 (1.7)	42 (0.9)	58 (0.8)	67 (0.8)	55 (1.0)	
Elixhauser comorbidity score, median (IQR)	5.0 (0.0–8.0)	5.0 (0.0–8.0)	5.0 (0.0–9.0)	5.0 (0.0–9.0)	5.0 (0.0–9.0)	0.51
No. of medications, mean±SD	10.1±4.6	10.6±4.6	11.0±4.7	11.3±4.8	11.8±5.0	<0.001
Length of stay, mean±SD	4.2±4.3	4.5±4.9	4.6±4.6	4.7±5.1	5.0±4.7	<0.001
Insurance type, n (%)						<0.001
Medicaid	18 (1.0)	107 (2.2)	198 (2.7)	43 (5.3)	705 (12.7)	
Medicare	1313 (70.0)	3473 (71.7)	5511 (74.7)	5865 (72.8)	3922 (70.8)	
Other	546 (29.1)	1263 (26.1)	1671 (22.6)	1757 (21.8)	915 (16.5)	
Heart failure	368 (19.6)	1055 (21.8)	1669 (22.6)	1904 (23.7)	1594 (28.8)	<0.001
Myocardial ischemia	575 (30.6)	1659 (34.3)	2755 (37.3)	3014 (37.4)	2205 (39.3)	<0.001
Atrial fibrillation	934 (49.8)	2129 (44.0)	2956 (40.1)	3134 (38.9)	1743 (31.5)	<0.001

IQR indicates interquartile range.
*Other indicates neither Black nor White.

risk for readmission that was 25% higher compared with those in the lowest quintile (hazard ratio [HR], 1.25; 95% CI, 1.03–1.51). For MI, patients in the highest ADI quintile had a 1-year risk for readmission that was more than twice that of those in the lowest quintile (HR, 2.04; 95% CI, 1.44–2.91). Contrary to HF and MI readmissions, AF readmissions were less likely with increasing ADI. Risk of 1-year readmission after index

Table 2. Incidence Rates Per 1000 Person-Years for Readmission by Diagnosis and Quintile of Area Derivation Index

	ADI Quintile					P Value
	1 (Least Deprived)	2	3	4	5 (Most Deprived)	
Readmission type						
Heart failure						
30 d	258.3 (188.7–353.5)	262.2 (216.0–318.4)	331.6 (288.3–381.5)	307.0 (267.1–352.9)	323.6 (274.8–381.0)	0.246
1 y	82.4 (69.7–97.5)	93.4 (84.6–103.1)	101.0 (93.5–109.1)	100.0 (92.9–107.8)	131.8 (121.8–142.5)	<0.001
Myocardial ischemia						
30 d	39.5 (17.7–87.9)	99.5 (72.7–136.2)	105.7 (82.6–135.3)	93.8 (73.0–120.6)	104.7 (78.6–139.3)	0.112
1 y	21.8 (15.8–30.1)	30.9 (26.1–36.6)	35.9 (31.6–40.8)	36.9 (32.7–41.6)	50.5 (44.6–57.2)	<0.001
Atrial fibrillation						
30 d	280.0 (206.9–378.9)	249.4 (204.4–304.3)	258.5 (220.6–302.8)	260.1 (223.6–302.5)	230.9 (190.4–280.1)	0.824
1 y	108.1 (93.2–125.4)	94.6 (85.7–104.4)	94.3 (87.0–102.2)	84.7 (78.2–91.9)	76.6 (69.1–84.8)	<0.001
Cardiac readmission						
30 d	795.9 (664.0–954.0)	944.4 (851.4–1047.7)	1080.4 (998.5–1169.1)	702.4 (639.7–771.3)	1086.4 (991.9–1189.2)	<0.001
1 y	311.1 (283.8–341.1)	326.8 (309.0–345.7)	354.2 (338.9–370.2)	345.7 (331.2–360.8)	413.1 (393.8–433.4)	<0.001
All-cause readmission						
30 d	1162.0 (1462.9–1888.1)	1939.4 (1801.3–2088.1)	2085.6 (1968.2–2210.0)	2123.8 (2010.1–2243.8)	2327.6 (2184.4–2480.3)	<0.001
1 y	647.9 (605.0–693.9)	711.9 (683.0–742.0)	713.7 (690.1–738.2)	745.7 (722.4–769.8)	901.8 (870.0–934.9)	<0.001

Data expressed as incidence rate (95% CI).

Table 3.   Cox Proportional Hazards Examining Risk of Readmission at 30 Days and 1 Year, Using Area Deprivation Index Quintile 1 as Referent for the Fully Adjusted Model

	ADI Quintile				
	1 (Least Deprived)	2	3	4	5 (Most Deprived)
Readmission type					
Heart failure					
30 d	1	0.96 (0.66–1.38)	1.17 (0.83–1.65)	1.06 (0.75–1.50)	0.99 (0.69–1.43)
1 y	1	1.06 (0.88–1.29)	1.11 (0.93–1.34)	1.08 (0.90–1.30)	1.25 (1.03–1.51)*
Myocardial ischemia					
30 d	1	2.46 (1.04–5.84)*	2.53 (1.09–5.84)*	2.22 (0.96–5.14)	2.33 (0.98–5.52)
1 y	1	1.38 (0.96–1.98)	1.55 (1.09–2.19)*	1.57 (1.12–2.22)†	2.04 (1.44–2.91)‡
Atrial fibrillation					
30 d	1	0.90 (0.63–1.30)	0.94 (0.67–1.32)	0.96 (0.68–1.34)	0.95 (0.66–1.38)
1 y	1	0.89 (0.74–1.06)	0.89 (0.75–1.05)	0.81 (0.68–0.95)*	0.79 (0.65–0.95)*
Cardiac readmission					
30 d	1	1.15 (0.93–1.41)	1.27 (1.05–1.55)*	1.19 (0.98–1.45)	1.19 (0.96–1.46)
1 y	1	1.01 (0.91–1.12)	1.06 (0.96–1.18)	1.03 (0.93–1.14)	1.13 (1.01–1.25)*
All-cause readmission					
30 d	1	1.12 (0.96–1.29)	1.16 (1.01–1.34)*	1.16 (1.01–1.33)*	1.22 (1.05–1.41)†
1 y	1	1.04 (0.96–1.13)	1.01 (0.93–1.09)	1.04 (0.96–1.12)	1.15 (1.06–1.24)‡

Model covariates include age, sex, race, ethnicity, Elixhauser comorbidity score, number of medications at discharge, length of stay at admission, and insurance as covariates. Data expressed as hazard ratio (95% CI).

*$P<0.05$.

†$P<0.01$.

‡$P<0.001$.

AF hospitalization was significantly lower for patients at higher ADI quintiles with risk decreasing in a stepwise fashion as ADI increased. Patients living in areas with the highest ADI were 21% less likely to be admitted within 1 year of index AF admission (HR, 0.79; 95% CI, 0.65–0.95). As ADI increased, risk of cardiac readmission increased at 1 year (HR, 1.13; 95% CI, 1.01–1.25) for the highest quintile compared with the lowest. Similarly, as ADI increased, risk of all-cause readmission increased at 30 days and 1 year (HR, 1.22; 95% CI, 1.05–1.41 and HR, 1.15; 95% CI, 1.06–1.24, respectively) for the highest quintile compared with the lowest. Figure 2 shows adjusted estimate curves for each readmission diagnosis.

The models incorporating ADI to predict 30-day and 1-year readmissions after HF diagnosis were best able to discriminate readmission from non-readmission, each with C-statistics of 0.70. Table 4 shows the absolute changes to C-statistic, NRI, and IDI indices for the fully adjusted multivariate model after adding ADI to the model across the clinical conditions in this study. Risk reclassification was significantly improved when including ADI to predict 30-day and 1-year readmission after AF hospitalizations and 1-year readmission after HF and MI hospitalizations. The model with ADI significantly predicted 1-year cardiac and all-cause readmissions by both NRI and IDI analyses.

ADI quintile was significantly associated with mortality. Patients in the highest ADI quintile were 25% more likely to die within a year (HR, 1.25 [1.08–1.44]). Using the fully adjusted model, we determined adjusted estimate curves for 1-year mortality for the entire cohort, stratified by ADI (see Figure 3.)

Outcomes were similar when using ADI as a continuous variable, as summarized by Table S4. While using ADI as a categorical variable, we performed sensitivity analyses to examine the separate effects of race, sex, and number of readmissions on the association between ADI and mortality. We found that the rate of 1-year readmission for women in the highest ADI quintile was significantly higher than that of men in the lowest quintile (P value for interaction=0.019). Other interactions between categorical race or sex and ADI were not statistically significant in multivariable-adjusted models and the results are otherwise consistent across subgroups, as seen in Table S5.

DISCUSSION

We identified that ADI is directly associated with disease-specific, cardiac, and all-cause readmission across 3 common cardiac admission diagnoses and is predictive of 1-year, all-cause mortality. These results persisted after adjusting for age, sex, race, comorbidity,
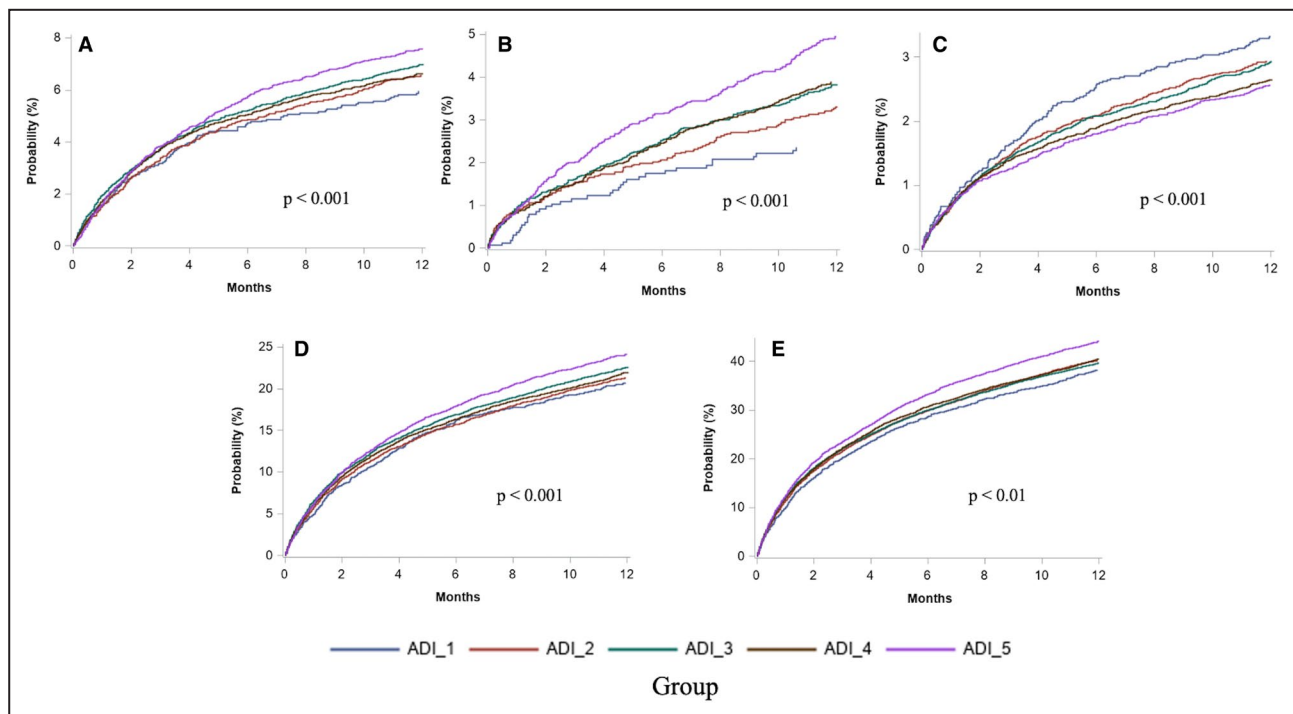
Figure 2.   Estimate curves for 1-year readmission stratified by area deprivation index in the fully adjusted model.
Model covariates included age, sex, race/ethnicity, Elixhauser comorbidity score, number of medications at discharge, length of stay at index admission, and insurance type. **A**, Cumulative heart failure readmission rate. **B**, Cumulative myocardial ischemia readmission rate. **C**, Cumulative atrial fibrillation readmission rate. **D**, Cumulative cardiac readmission rate. **E**, Cumulative all-cause readmission rate. ADI indicates area deprivation index.

number of medications at discharge, length of stay at index admission, and insurance type. In addition to evaluating the C-statistic, our work used NRI and IDI to assess risk using ADI in the fully adjusted multivariable model. The findings underscore the importance of identifying markers of patient disadvantage at the time of inpatient hospital admissions.

In the present study, patients in the highest ADI quintile had a significantly higher 1-year risk for HF readmission compared with those in the lowest quintile. Previous studies have shown that markers of neighborhood deprivation are associated with HF outcomes.[4,25,26] A prior study showed that median neighborhood income contributes to the risk for HF readmission and death, especially for those with higher medical comorbidity.[4] Another study showed that for patients with HF, neighborhood deprivation was significantly associated with all-cause readmission even after accounting for patients' individual SES.[25] Our study adds to the HF readmission literature because we showed that neighborhood deprivation is associated with readmission and mortality, but also that a model with ADI predicts risk better than models without ADI. According to a recent scientific statement from the American Heart Association, SDOH (including neighborhood resources) should be collected and assessed as an essential part of routine HF care.[27] Our

work demonstrated a practical and feasible approach to leverage available data that can be integrated into the clinical care of a patient population.

We have shown that the models for risk of HF 30-day and 1-year readmissions perform well, as evidenced by C-statistics of 0.70. In addition, the predictive model for 1-year MI readmission performs well when area deprivation is accounted for, as evidenced by C-statistic of 0.66 and significant NRI and IDI. A recent population-based study showed that people of low SES have risk of coronary heart disease above what is projected by traditional risk factors.[28] Mechanisms underlying this relationship may include increased rates of obesity,[29] tobacco use,[30] and exposure to environmental pollution[31] all of which conspire to worsen outcomes in individuals with lower SES. Additionally, a cross-sectional study using Medicare data showed a negative association between ADI and receipt of drug eluting stent for coronary artery disease which illustrates variation in care by ADI for patients hospitalized for MI.[32]

In our study, incidence of hospital readmission increased with worsened neighborhood deprivation for HF and MI readmissions, but there was an inverse relationship between ADI and readmission rate for AF. In spite of the decreased rates of readmission for AF, the overall cardiac and all-cause readmission rates increased with higher ADI. Likewise, increasing ADI was

Table 4. C-Statistic, Continuous Net Reclassification Index, and Integrated Discrimination Improvement Indices for the Fully Adjusted Multivariate Model That Includes Area Deprivation Index

Diagnosis	C-Statistic	Change in C-Statistic		Continuous NRI	Change in NRI		IDI	Change in IDI	
		Mean (SE)	P Value	Mean (95% CI)	Mean (SE)	P Value	Mean 95% CI	Mean (SE)	P Value
Heart failure									
30 d	0.697	0.0005 (0.002)	0.804	0.047 (−0.028, 0.122)	0.0472 (0.0383)	0.224	0.0002 (0, 0.0004)	0.0002 (0.0001)	0.092
1 y	0.696	0.0008 (0.0006)	0.228	0.105 (0.065, 0.144)	0.1047 (0.0201)	<0.001	0.0003 (0, 0.0006)	0.0003 (0.0002)	0.093
Myocardial ischemia									
30 d	0.655	0.0092 (0.0078)	0.241	0.093 (−0.030, 0.218)	0.0937 (0.0632)	0.170	0.0002 (0.0001, 0.0004)	0.0002 (0.0001)	0.007
1 y	0.659	0.0036 (0.0032)	0.270	0.153 (0.088, 0.219)	0.1531 (0.0335)	<0.001	0.0012 (0.0007, 0.0016)	0.0012 (0.0002)	<0.001
Atrial fibrillation									
30 d	0.600	0.0002 (0.003)	0.945	0.078 (0.035, 0.123)	0.0789 (0.0224)	0<0.001	0.0005 (0.0002, 0.0008)	0.0005 (0.0002)	<0.001
1 y	0.589	0.0018 (0.0016)	0.271	0.079 (0.035, 0.123)	0.0789 (0.0225)	<0.001	0.0005 (0.0002, 0.0008)	0.0005 (0.0001)	<0.001
Cardiac readmission									
30 d	0.600	0.0001 (0.0014)	0.933	0.009 (−0.032, 0.05)	0.0089 (0.021)	0.690	0.0003 (0.0001, 0.0005)	0.0003 (0.0001)	0.009
1 y	0.608	0.0002 (0.0004)	0.633	0.065 (0.039, 0.092)	0.0651 (0.0135)	<0.001	0.0005 (0.0002, 0.0007)	0.0005 (0.0001)	<0.001
All-cause readmission									
30 d	0.639	0.0003 (0.0004)	0.528	0.004 (−0.027, 0.035)	0.0039 (0.0158)	0.812	0.0003 (0, 0.0006)	0.0003 (0.0001)	0.022
1 y	0.638	0.0004 (0.0003)	0.167	0.085 (0.063, 0.107)	0.0852 (0.0113)	<0.001	0.0012 (0.0008, 0.0016)	0.0012 (0.0002)	<0.001

IDI indicates integrated discrimination index; and NRI, net reclassification index.
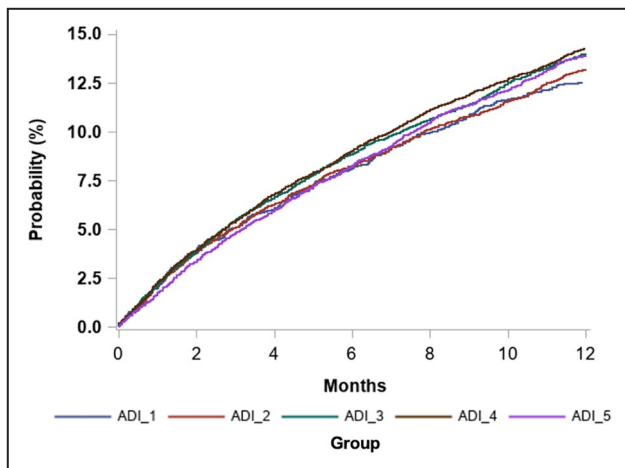
Figure 3. Estimate curve for 1-year mortality stratified by area deprivation index in the fully adjusted model.
Model covariates included age, sex, race/ethnicity, Elixhauser comorbidity score, number of medications at discharge, length of stay at index admission, and insurance type. ADI indicates area deprivation index.

associated with worse all-cause mortality. Therefore, a low likelihood of AF readmission among those living in deprived areas was not protective and was associated with worse outcomes. We are not the first to show a relatively higher prevalence of AF among higher income groups, a pattern that has emerged in other large data sets.[33,34] The underlying contributors to lower AF admissions for people of socioeconomically disadvantaged backgrounds are likely multifaceted. One possibility could involve limited access to specialty care. Other studies have shown that people living in low-resource neighborhoods more frequently seek care in emergency departments rather than other means of outpatient care.[35] However, we did not find any differences in emergency department use by cardiac diagnoses or by ADI. A second possible reason for lower AF readmission rates with worse ADI could relate to lower rates of detection among people with less resources.[36] Therefore, people living in areas with low ADI might also be less likely to have an AF readmission. Third, the observed associations with ADI and SES likely overlap with racial disparities in AF care. Multiple reports have indicated the decreased incidence of AF in individuals of Black race.[37] In general, however, such studies have had limited consideration or adjustment of social factors, the built environment, or indicators of structural racism, all of which we would expect to influence access to healthcare services and subsequent screening and detection of conditions such as AF. Reports of increased adversity in individuals of Black race with AF relative to White patients likewise may not have considered structural factors and access to treatment.[38] Our work suggests that greater attention towards AF, healthcare access, and

structural barriers is critical towards understanding the relationship between AF admissions and ADI.

ADI encompasses multiple socioeconomic variables and, like a biomarker, can add to risk prediction for cardiac outcomes, but the mechanisms of this association deserve further exploration. Socioeconomic deficits may complicate adherence to medications or the ability to attend clinic appointments, as individuals struggle to choose between material necessities and medical care.[39] Low SES yields decreased access to prescription medications[5,39] and results in competing material priorities for using health services.[40] Social and economic disparities—income, chronic disease burden, food access, pollution, and others—have strong associations with increased risk for adverse outcomes in individuals with cardiovascular and other conditions.[35,41–44] Area deprivation therefore likely reflects individual SES, but also can begin to illuminate the deeper, more important aspects of a patient's unmet social needs.[45] Notably, a prior study used machine learning to evaluate the predictive ability of neighborhood SES on risk of hospitalization, but was null.[35]

Living in a socioeconomically disadvantaged neighborhood has been previously linked with worse clinical outcomes for a range of health conditions, including higher mortality.[14,41,46] Authors have previously demonstrated a link between neighborhood ADI and hospital readmission for HF and MI.[17] Our results support the prior study's determination that ADI carries as much risk for readmission as would the addition of another chronic medical illness.[17] Our work adds to this body of literature by showing that ADI, in combination with EHR data, can predict adverse risk for individual patients. Overall, the available evidence links neighborhood deprivation and individuals' risk for hospitalization. Moreover, from a more general health system perspective, ADI has been associated with poor hospital performance in the national hospital readmission reduction program.[47,48] Authors demonstrate that hospitals in economically depressed locations of the United States face higher rates of readmission.[48]

Healthcare systems have acknowledged the importance of assessing social determinants of health and have advocated for assessing patient needs in the medical record.[49,50] This study has supported ADI's predictive ability for individual patients and ease of incorporation into a multivariable model, in part because ADI can be derived from data available in the medical record. Healthcare systems can incorporate ADI scores as a marker of disadvantage for all patients to assess risk of clinically important outcomes and to allocate resources at the time of hospital discharge. Our sensitivity analyses underscore the importance of limiting the number of readmissions for people living in the most deprived areas because of a mortality benefit in the year subsequent to index admission. A future

intervention might include the strategic placement of and referral to cardiac rehabilitation facilities in locations otherwise lacking resources in an effort to prevent readmission for higher risk cardiac patients.[51]

Our analysis had several strengths. A large proportion of our cohort lived in areas with the most deprivation, allowing us to fully capture the effect that deprivation has on a historically marginalized segment of the population. Our assessment of a regional healthcare system includes patients living in different states and in urban and exurban locations. This work shows the benefit of a system-wide application of a deprivation measure to accurately estimate risk for individual patients, an example of how hospital systems can use available SDOH data to inform patient care.

Our study has several important limitations. First, although ADI is a comprehensive and validated measure of neighborhood-level social determinants of health, some important measures are not included. For example, scholars have cited other neighborhood-level contributors that correlate closely with disease outcomes, like racial segregation, area crime rates, difficulty within the built environment, or limited green space.[52,53] In addition, ADI is a composite of 17 facets of deprivation and likely overlaps with other social determinants like race or insurance. However, we did not find multicollinearity in our model. Second, we conducted our study within a single regional healthcare system. As a result, generalizability of our findings to other geographic or more racially diverse settings may be limited. However, we expect that ADI would have similar contributions to healthcare access, readmission, and outcomes in other settings, such as those with more urban density or a greater proportion of minoritized individuals. Third, the diagnoses were not clinically adjudicated. Authors have recognized the limitations of EHR administrative data as a proxy for clinical diagnoses.[54] We note that in our study, diagnoses were derived uniformly from administrative records without regard to ADI status. Consequently, we expect that misclassification of diagnosis would be non-differential with respect to ADI and thereby bias our results towards the null. Fourth, inability to ascertain comprehensive follow-up, as individuals may have moved or had events outside of our healthcare system. Similarly, because we excluded patients that died either in hospital or died as an outpatient in the analysis for readmission risk, there is a concern for immortal time bias or underestimation of the readmission event risk. However, if these patients had no readmission before death, the date of death was used as the censoring time for the readmission event. Fifth, we are not able to exclude residual confounding. Multiple factors not included in our analysis, such as environmental exposures, adherence, access to primary and specialized care, and community-based support may contribute towards the association

of ADI and health outcomes. Sixth, using the NRI and IDI methodology our models showed incremental improvement with the addition of ADI, but some have suggested that NRI is a less robust method than the C-statistic.[55] Nevertheless, the addition of ADI has significantly contributed to our analysis of patient risk, irrespective of analytical approach.

In conclusion, residence within a socioeconomically disadvantaged community can contribute to prediction of rehospitalization. Measures of neighborhood deprivation, such as ADI, should be used to inform targeted interventions to higher risk groups as well as future practice and policy. In this analysis, we model how EHR could readily incorporate relevant social factors into risk stratification for readmission. By doing so, health systems can better identify patients at risk for poor outcomes and better allocate needed resources in the post-hospitalization period.

ARTICLE INFORMATION

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Supplementary Material

Tables S1–S5

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SUPPLMENTAL MATERIAL

Table S1. International Classification of Diseases, 9th and 10th revision (ICD-9 and ICD-10) codes used to determine cardiac diagnoses from the electronic health record.

Diagnosis	ICD codes
Heart Failure	
ICD-9	428, 428.0, 428.1, 428.2, 428.2, 428.21, 428.22, 428.23, 428.3, 428.30, 428.31, 428.32, 428.33, 428.4, 428.40, 428.41, 428.42, 428.43, 428.9
ICD-10	I50, I50.1, I50.2, I50.20, I50.21, I50.22, I50.23, I50.3, I50.30, I50.31, I50.32, I50.33, I50.4, I50.40, I50.41, I50.42, I50.43, I50.8, I50.81, I50.810, I50.811, I50.812, I50.813, I50.814, I50.82, I50.83, I50.84, I50.89, I50.9
Myocardial Ischemia	
ICD-9	410.01, 410.11, 410.21, 410.31, 410.41, 410.51, 410.61, 410.71, 410.81, 410.91
ICD-10	I21.01, I21.02, I21.09, I21.11, I21.19, I21.21, I21.29, I21.3, I21.4, I21.9, I21.A1, I21.A9, I22.0, I22.1, I22.2, I22.8, I22.9
Atrial Fibrillation	
ICD-9	427.31, 427.32
ICD-10	I48.0, I48.1, I48.2, I48.91, I48.3, I48.4, I48.92

Table S2. Cox proportional hazards examining risk of readmission at 30 days and one year, using area deprivation index (ADI) quintile 1 as referent. Model 1 includes age, sex race and ethnicity as covariates. Data expressed as HR (95% confidence interval).

		ADI Quintile				
		1 **(least deprived)**	**2**	**3**	**4**	**5** **(most deprived)**
Readmission type						
Heart Failure	30 days	1	1.03 (0.71-1.48)	1.29 (0.92-1.82)	1.22 (0.87-1.72)	1.19 (0.83-1.72)
	1 year	1	1.14 (0.94-1.38)	1.22 (1.02-1.47) *	1.23 (1.02-1.47) *	1.47 (1.21-1.78) ‡
Myocardial Infarction	30 days	1	2.54 (1.07-5.99) *	2.68 (1.16-6.19) *	2.43 (1.05-5.61) *	2.67 (1.13-6.33) *
	1 year	1	1.42 (0.99-2.05)	1.65 (1.17-2.33) †	1.73 (1.23-2.45) †	2.37 (1.66-3.36) ‡
Atrial Fibrillation	30 days	1	0.89 (0.62-1.28)	0.91 (0.65-1.28)	0.92 (0.66-1.31)	0.90 (0.62-1.29)
	1 year	1	0.87 (0.73-1.04)	0.86 (0.73-1.02)	0.78 (0.66-0.92) †	0.73 (0.61-0.88) †
Cardiac readmission	30 days	1	1.19 (0.97-1.47)	1.36 (1.11-1.65) †	1.29 (1.06-1.58) *	1.33 (1.08-1.64) †
	1 year	1	1.05 (0.94-1.17)	1.13 (1.02-1.25) *	1.11 (1.00-1.23) *	1.26 (1.13-1.40) ‡

All-cause readmission	30 days	1	1.17 (1.01-1.36) *	1.25 (1.09-1.44) †	1.30 (1.13-1.49) ‡	1.41 (1.22-1.63) ‡
	1 year	1	1.10 (1.01-1.19) *	1.09 (1.01-1.17) *	1.15 (1.07-1.24) ‡	1.32 (1.22-1.43) ‡

*p<0.05, † p<0.01, ‡p<0.001

Table S3. **Cox proportional hazards examining risk of readmission at 30 days and one year, using area deprivation (ADI) quintile 1 as referent.** Model 2 includes age, sex race and ethnicity and Elixhauser comorbidity score as covariates. Data expressed as HR (95% confidence interval).

ADI Quintile						
		1 (least deprived)	2	3	4	5 (most deprived)
Readmission type						
Heart Failure	30 days	1	1.01 (0.70-1.46)	1.26 (0.89-1.78)	1.19 (0.84-1.68)	1.16 (0.80-1.67)
	1 year	1	1.12 (0.92-1.36)	1.19 (0.99-1.43)	1.19 (0.99-1.43) *	1.41 (1.17-1.71) ‡
Myocardial Infarction	30 days	1	2.55 (1.08-6.01) *	2.69 (1.17-6.22) *	2.44 (1.05-5.65) *	2.69 (1.14-6.38) *
	1 year	1	1.42 (0.99-2.05)	1.65 (1.17-2.33) †	1.73 (1.23-2.44) †	2.36 (1.66-3.36) ‡
Atrial Fibrillation	30 days	1	0.89 (0.62-1.27)	0.91 (0.65-1.28)	0.92 (0.66-1.29)	0.89 (0.61-1.28)
	1 year	1	0.87 (0.73-1.04)	0.86 (0.72-1.01)	0.77 (0.65-0.91) †	0.72 (0.60-0.87) ‡
Cardiac Readmission	30 days	1	1.18 (0.96-1.46)	1.34 (1.10-1.63) †	1.28 (1.05-1.56) *	1.31 (1.07-1.62) †
	1 year	1	1.04 (0.93-1.16)	1.11 (1.00-1.23) *	1.09 (0.99-1.21)	1.23 (1.10-1.37) ‡
All-cause readmission	30 days	1	1.16 (1.00-1.35) *	1.24 (1.08-1.42) †	1.28 (1.11-1.47) ‡	1.38 (1.19-1.60) ‡
	1 year	1	1.08 (1.00-1.17) *	1.07 (0.99-1.16)	1.13 (1.05-1.22) ‡	1.29 (1.19-1.40) ‡

*p<0.05, † p<0.01, ‡p<0.001

Table S4. Sensitivity analyses using the area deprivation index (ADI) as a continuous variable as a predictor of readmissions in the fully adjusted model.

Diagnosis	Readmission time period	Hazard ratio	P-value
Heart failure	30 days	1.00 (0.996-1.003)	0.850
	1 year	1.002 (1.000-1.004)	0.018
Myocardial ischemia	30 days	1.003 (0.997-1.009)	0.320
	1 year	1.007 (1.004-1.01)	<0.001
Atrial fibrillation	30 days	1.00 (0.996-1.004)	0.987
	1 year	0.997 (0.995-0.999)	0.002
Cardiac readmission	30 days	1.001 (0.999-1.003)	0.380
	1 year	1.001 (1.000-1.002)	0.014
All-cause readmission	30 days	1.002 (1.000-1.003)	0.012
	1 year	1.002 (1.001-1.002)	<0.001
Mortality	30 days	1.002(0.998-1.005)	0.357
	1 year	1.003(1.002-1.004)	<0.001

Table S5. Sensitivity analyses testing the interactions for area deprivation index (ADI) by race and for ADI by sex in the fully adjusted model.

Readmission type	Interaction	DF	Wald Chi-Square	Probability > χ^2
Heart failure				
30 days	ADI quintile x Race	8	1.46	0.993
	ADI quintile x Sex	4	2.70	0.609
1 year	ADI quintile x Race	8	5.59	0.694
	ADI quintile x Sex	4	1.63	0.804
Myocardial ischemia				
30 days	ADI quintile x Race	8	0.340	1.0
	ADI quintile x Sex	4	3.16	0.532
1 year	ADI quintile x Race	8	2.23	0.973
	ADI quintile x Sex	4	11.80	0.019
Atrial fibrillation				
30 days	ADI quintile x Race	8	1.87	0.985
	ADI quintile x Sex	4	6.36	0.174
1 year	ADI quintile x Race	8	12.15	0.144
	ADI quintile x Sex	4	2.73	0.604

DF = degrees of freedom