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SCHOOL OF MEDICINE – GRADUATE STUDIES

Correlation of 2015 and 2021 Area Deprivation Index (ADI) to Acute and Chronic Health Measures

By
Valerie L. Welch, M.D.

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Dedicated to my family and my mentors, Ben Orwoll, MD, and Daniel Fort, PhD, who have believed in me and supported me throughout this journey.

Introduction

Epidemiological studies have long focused on identifying risk factors for human disease. Researchers in the 20th century were successful in identifying risk factors, such as smoking and diet,(1) which serve as targets for internal change with the end goal of mitigating or preventing disease. However, in recent decades, research has evolved into identifying social conditions and social factors which may serve as targets of external change to mitigate or prevent disease. Researchers Link and Phelan believe that "social factors such as socioeconomic status and social support are likely 'fundamental causes' of disease that, because they embody access to important resources, affect multiple disease outcomes through multiple mechanisms, and consequently maintain an association with disease even when intervening mechanisms change."(2) This paper will explore socioeconomic status and individual rates of disease.

Neighborhood Deprivation Indices Created in the Early 2000s

To assess the impact of socioeconomic factors on human disease, researchers in the late 20th century needed to figure out how to obtain socioeconomic data on a population-wide scale in the U.S. Gopal Singh, PhD, a Senior Health Equity Advisor at the U.S. Department of Health and Human Services, recognized a deficiency in socioeconomic data as it relates to U.S. mortality statistics, so he set out to create an index of area deprivation. His goal was to develop a census-based socioeconomic index that would link to U.S. mortality statistics and allow for tracking health inequities now and over time. While Dr. Singh recognized that single measures, such as income level or median home value, could be used to classify an area, he believed that creating a composite index with multiple key measures would better reflect the multidimensional characterization of an area's socioeconomic status.(3)

Dr. Singh initially identified 21 socioeconomic indicators, drawn from the 1990 U.S. Census and selected based on theoretical relevance and prior research, to create his index of area deprivation. These socioeconomic indicators included educational distribution (i.e. percentage of the population with less than 9 years and with 12 or more years of education); median family income; income disparity; occupational composition; unemployment rate; family poverty rate; percentage of the population below 150% of the poverty rate; single-parent household rate; home ownership rate; median home value; median gross rent; median monthly mortgage; household crowding; percentages of households without access to a telephone, plumbing, or motor vehicles; English language proficiency; divorce rate; percentage of urban population; and percentage of immigrant population.(3)

Using Factor Analysis, Dr. Singh determined that one of two main factors accounted for 43% of the variance in the data, and that 17 of the 21 indicators had a larger impact on that factor. English language proficiency, percentage of urban population, and percentage of immigrant population did not have a significant impact on the aforementioned factor, and the divorce rate did not have a significant impact on either of the two main factors. Thus, these four indicators were eliminated from consideration and the index was created by turning the remaining 17 socioeconomic indicators into a single factor solution.(3)

Dr. Singh created his index with an arbitrary mean of 100 and standard deviation of 20, and the index values were calculated for all 3,097 U.S. counties/parishes. When the 1990 U.S. Census data was converted into the 1990 county index, the scores ranged from 70.22 to 160.32, with the higher scores indicating greater levels of deprivation. Greater deprivation was indicated by lower median family income, higher unemployment rate, low home ownership rate, and higher percentages of households without plumbing, for example. The correlation of the index with infant mortality rate was 0.48, while the correlation with low birthweight rate was 0.46. Interestingly, there was no statistically significant relationship between race and area deprivation.(3)

While Dr. Singh was creating his composite index from 1990 U.S. Census data,(3) Lynne Messer and colleagues were working to create a neighborhood deprivation index using the birth outcomes and maternal characteristics from birth certificates (select years between 1995 and 2001) and tract level Census of Population and Housing Data from the year 2000 (from the U.S. Census Bureau). They considered 20 different census variables across seven broad socioeconomic and demographic domains that had been associated with health outcomes in prior studies. Using principal components analysis (PCA) and their own criteria for calculated loadings, they chose eight of the 20 variables for the index: "percent of males in management and professional occupations, percent of crowded housing, percent of households in poverty, percent of female headed households with dependents, percent of households on public assistance and households earning < $30,000 per year as a surrogate for poverty, percent earning less than a high school education, and percent unemployed." The health measures they selected for index creation were low birth weight and preterm birth for singleton gestations, and they categorized deprivation scores into quartiles. The calculated deprivation index was standardized such that the mean was 0 with a standard deviation of 1. They included eight geographic areas in the study: three urban centers (Philadelphia, PA, Baltimore City, MD, and 16 pooled cities in Michigan) and five counties they deemed to be racially heterogeneous – three Maryland counties near Washington, DC, and Baltimore, MD, plus two counties in North Carolina.(4)

The results showed that each component contributed nearly equally to the overall neighborhood deprivation index in this study. Additionally, the component loadings were consistent across locations, despite the geographic and socioeconomic variability. The contribution of unemployment, for example, to the deprivation index in Philadelphia was as important as its contribution to the deprivation index in a county in North Carolina. Another important pattern was the consistency of factor loadings on the overall deprivation score. The overall neighborhood deprivation index consisted of a weighted average of the component variables from the various geographic/socioeconomic units, and the authors propose that the deprivation index may be broadly applicable to other geographic areas. The authors promote the use of a composite index because variability in deprivation score is reduced when there are changes in a single variable. Despite the limitations of the study, the authors conclude that neighborhoods where women live are likely sources of both support and stress, and that the neighborhood influences may reasonably affect birth outcomes.(4)

Creation of the Current Area Deprivation Index

Amy Kind, MD, PhD, and her team at the University of Wisconsin – Madison refined Dr. Singh's index of area deprivation to create the Area Deprivation Index (ADI), which is now widely used as a surrogate for socioeconomic disadvantage. The ADI's primary objective is to characterize geographic areas by socioeconomic advantage or disadvantage.(5) In contrast to Dr. Singh's county-level deprivation index,(3) Dr. Kind and team's ADI has been validated to the census block group level, which typically contains between 600 and 3000 people,(6) and is not recommended for use with other geographic levels, such as zip code or county/parish. Index values are available at both the state and national level.(5)

American Community Survey

The ADI in its current state is based on American Community Survey (ACS) data.(7) In contrast to the United States Census "short form," which is mandated by the United States

Constitution and completed every 10 years, the ACS "long form" is conducted on a continuous basis. That is, while the U.S. Census serves to gather basic information about each person living in each household across the country once each decade, the ACS seeks to obtain far more detailed data from a smaller number of households at a shorter interval. Each month, the ACS is sent to about 3.5 million addresses in all 50 states, the District of Columbia, and Puerto Rico,(8) and the response rate has ranged from 71.2% to 92.0% in the most recent five years data is available (2018 to 2022).(9)

The following figures provide more information about the function and purpose of the ACS. Figure 1 shows how the information gathered from individual households is processed and ultimately used by the government to apportion social services and assess regional infrastructure needs, for example. Figure 2 provides a detailed list of the subjects covered by the ACS and the types of products that are generated with ACS data. Figure 3 shows how the country is broken down geographically, with the smallest geographic area being the census block group.(10)

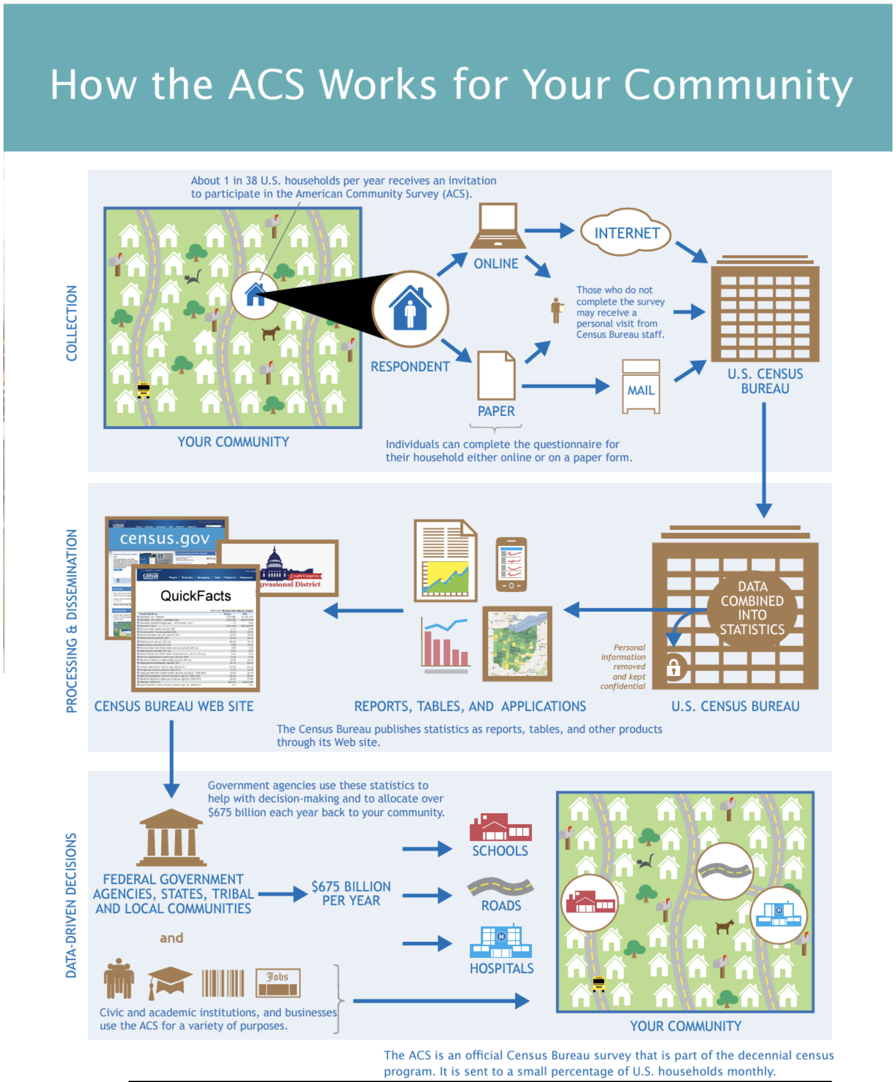

Figure 1. From the American Community Survey Information Guide, page 3

ACS Subjects and Data Products

Population

Age
Ancestry
Citizenship Status
Commuting (Journey to Work) and Place of Work
Disability Status
Educational Attainment and School Enrollment
Employment Status
Fertility
Grandparents as Caregivers
Health Insurance Coverage
Hispanic or Latino Origin
Income and Earnings
Industry, Occupation, and Class of Worker
Language Spoken at Home
Marital History, Marital Status
Migration/Residence 1 Year Ago
Period of Military Service
Place of Birth
Poverty Status
Race
Relationship to Householder
Sex
Undergraduate Field of Degree
VA Service-Connected Disability Status
Veteran Status
Work Status Last Year
Year of Entry

Housing

Acreage and Agricultural Sales
Bedrooms
Computer and Internet Use
Food Stamps/Supplemental Nutrition Assistance Program (SNAP)
House Heating Fuel
Kitchen Facilities
Occupancy/Vacancy Status
Occupants Per Room
Plumbing Facilities
Rent
Rooms
Selected Monthly Owner Costs
Telephone Service Available
Tenure (Owner/Renter)
Units in Structure
Value of Home
Vehicles Available
Year Householder Moved Into Unit
Year Structure Built

Key ACS Data Products

Data Profiles
Provide broad social, economic, housing, and demographic profiles.

Comparison Profiles
Similar to Data Profiles but show data side-by-side from the five most recent years of the ACS.

Selected Population Profiles
Provide broad social, economic, housing, and demographic profiles for a large number of race, ethnic, ancestry, and country/region of birth groups.

Ranking Tables
Provide state rankings of estimates across 86 key variables.

Subject Tables
Similar to Data Profiles but include more detailed ACS data, classified by subject.

Detailed Tables
Provide access to the most detailed ACS data and cross tabulations of ACS variables.

Geographic Comparison Tables
Compare geographic areas other than states (e.g., counties or congressional districts) for key variables.

Summary Files
Provide access to the Detailed Tables through a series of comma-delimited text files.

Public Use Microdata Sample (PUMS) Files
Provide access to ACS microdata for data users with statistical software experience.

Figure 2. From the American Community Survey Information Guide, page 10

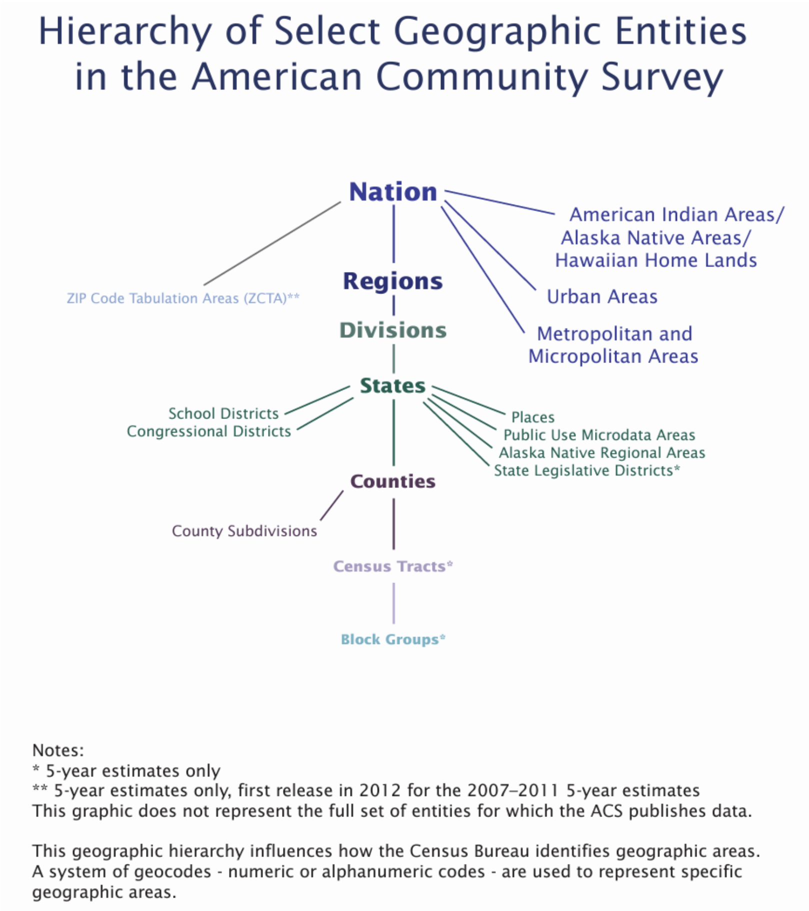

Figure 3. From the American Community Survey Information Guide page 11

Area Deprivation Index Defined

The ADI incorporates 17 measures from four domains – income, housing, employment, and education (see Table 1).(11) Each year's version of the ADI uses composite ACS data from the prior five years (including the named year). Once calculated, the composite ADI score is made available in percentiles, 1 to 100, nationally, and deciles, 1 to 10, for states. The national ADI ranks individual census block groups against all the other census block groups in the United States, while the state ADI ranks individual census block groups against all the other census block groups in that state. The higher the number, the greater the deprivation, and each census block group is assigned both a national ADI percentile score and a state ADI decile score.(5)

Table 1. Area Deprivation Index (ADI) - ACS Variables Included	
Domain	Measure
Income	Median family income (US dollars)
	Income disparity
	Percentage of families below the poverty level
	Percentage of population below 150% of the poverty threshold
Education	Percentage of population aged 25 years or older with less than 9 years of education
	Percentage of population aged 25 years or older with less than a high school diploma
Employment	Percentage of civilian labor force population aged 16 years or older unemployed (unemployment rate)
	Percentage of employed persons aged 16 years or older in white collar occupations
Housing	Median home value (US dollars)
	Median gross rent (US dollars)
	Median monthly mortgage (US dollars)
	Percentage of owner-occupied housing units (home ownership rate)
	Percentage of single-parent households with children younger than 18 years
	Percentage of households without a motor vehicle
	Percentage of households without a telephone*
	Percentage of occupied housing units without complete plumbing
	Percentage of households with more than 1 person per room (crowding)

***Replaced with Percentage of households without internet beginning with the 2020 ADI**

By way of example, the State of Louisiana is used to demonstrate the distribution of state and national ADI values. The Louisiana state ADI heatmap (Figure 4) generally demonstrates that the least disadvantaged groups, identified by blue and dark blue on the heatmap, are concentrated in smaller geographic areas, while the most disadvantaged groups, identified by orange and red, are located in larger presumably more rural geographic areas. The national ADI heatmap for Louisiana (Figure 4) shows a sharp contrast, with the majority of the state being more disadvantaged, as shown by the larger percentage of dark red and orange on the heatmap, with only a few areas across the state showing as light blue, or less disadvantaged. Noticeably, the darkest blue color (least disadvantaged, ADI of 1 to 10) is almost completely absent on the national ADI heatmap for the State of Louisiana. The heatmaps show that when the State of

Louisiana is compared to the entire nation, Louisiana on the whole has greater deprivation than the rest of the country.(12)

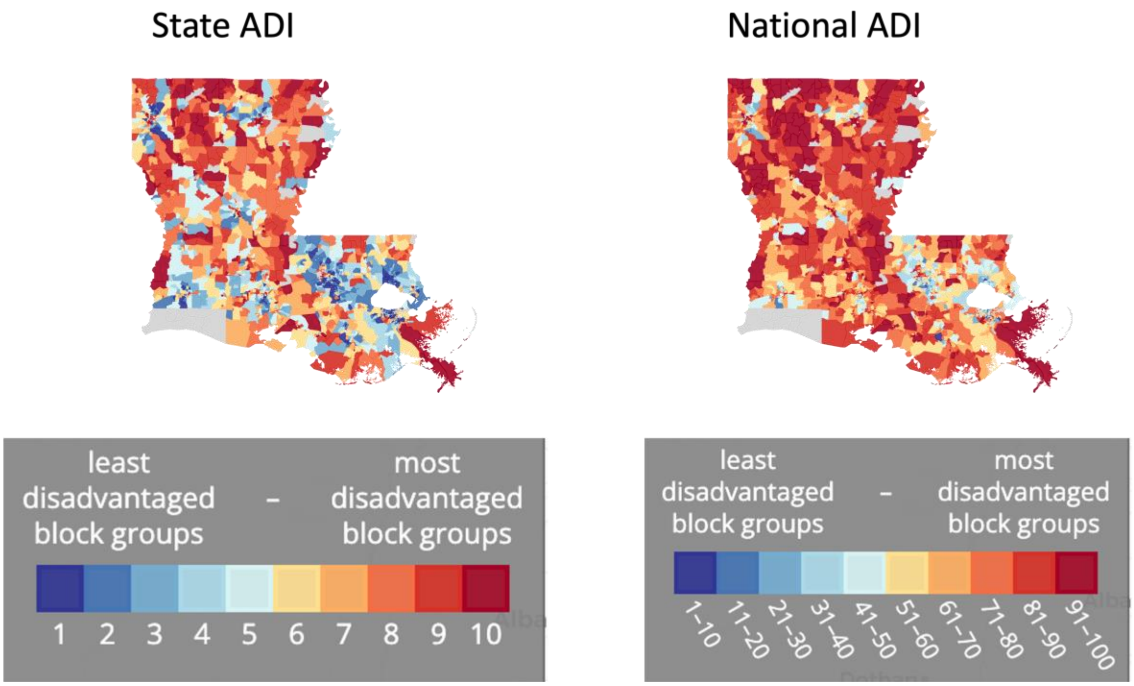

Figure 4. From: https://www.neighborhoodatlas.medicine.wisc.edu/mapping

Documenting Changes in the Area Deprivation Index Over Time

The Neighborhood Atlas® publishes a changelog documenting the differences in ADI versions over time. The 2015 ADI (v3.0) values, made available 4/1/2020, were based off the 5-year estimates from the 2011-2015 ACS and incorporated suppression and imputation criteria that entered use with the 2018 version (published 11/19/2020) and were subsequently retroactively applied to the 2015 ADI data. Block group suppression criteria, attributed to Diez-Roux and colleagues, includes suppressing "any block group with fewer than 100 persons, fewer than 30 housing units, or greater than 33% of the population living in group quarters."(13) A small number of block groups were also suppressed due to survey errors identified by the U.S.

Census Bureau. The Neighborhood Atlas® team also used a geographically-nested imputation methodology, similar to those used in other deprivation indices (English Indices of Multiple Deprivation, or IMD, and Scottish Indices of Multiple Deprivation, or SIMD), to handle missing ACS items.(14)

Beginning with the 2020 ADI, the “no phone” variable was removed and replaced with the “no household internet” variable to reflect current trends. This version also used the redrawn 2020 census block groups, which feature an increase in block groups from ~220,000 to ~245,000 persons. The reapportionment of the block groups included changing geographic boundaries, which is thought to make comparison of the 2020 ADI with previous ADI versions impossible. The 2021 ADI (version 4) is based on the 2017-2021 ACS data and included minor statistical updates to mitigate year-to-year sampling variations from the ACS data (intended to buffer from known/future expected variation in ACS data). The 2021 v4.0.1 ADI data is based on 2017 – 2021 ACS 5-year estimates and the 2021 census block groups and 2021 nine-digit ZIP code centroids.(14)

Deprivation Index Best Practices

More than a decade after Singh and Messer and colleagues created their own area/neighborhood deprivation indices, Allik and colleagues published guidelines for creating a small-area deprivation index. The framework they laid out included five key stages:

1. Selection of appropriate data and geographic area.
2. Selection of individual deprivation indicators.
3. Constructing the index: combining and weighting indicators.
4. Validation and sensitivity analysis.
5. Dealing with uncertainty.

The authors urge researchers to justify their decisions at each stage in the process, so that others may understand the strengths and limitations of the index. One of the major pitfalls in the process of creating an area deprivation index is the scarcity of methods available for validating that index, and Allik and colleagues suggest that testing the deprivation indicators against health outcomes might be one of the best validation methods. The authors postulate that “indicators that are best at distinguishing between the different levels of deprivation are those that are also best at describing the variation in health.” Even so, different socioeconomic indicators are not equally effective in explaining health inequalities for different subsets of the population; thus it is crucial to validate indices across varying populations.(15)

ADI Validation Studies

In alignment with Allik and colleagues’ suggestion to validate small-area deprivation indices against health outcomes,(15) numerous researchers have compared area/neighborhood deprivation indices to various health outcomes. Maroko, et al, evaluated the strength of the association between hospitalization rates and ADI in the Hudson Valley region of New York. Using data from the year 2000, the authors used zip code tabulation areas (ZCTAs) as the base geographic area for their own “local-scale ADI” and calculated 10 km radius, 20 km radius, 30 km radius, and regional values. The ADI values were considered high if in the top 15% and low if in the bottom 85%. The odds ratios calculated showed that the smallest geographical area (10 km radius) had the strongest association between ADI and hospitalization rate, making an excellent argument for use of ADI in the context of the smallest geographic area possible (while still maintaining individual anonymity). The authors postulated that flagging for deprivation, perhaps in the electronic health record, could help with social determinants of health evaluation and community resource allocation.(16)

Dr. Amy Kind and colleagues used Dr. Singh's area deprivation index (ADI) at the census block group level to evaluate 30-day rehospitalization risk in association with neighborhood disadvantage. Using hospitalization data from 2004 to 2009, they showed that those who were in the top 15% of area deprivation (most deprived) were at a higher risk of rehospitalization than those in the bottom 85% of area deprivation (least deprived). The bottom 85% had an average 30-day rehospitalization rate of 21%, while the top 15% had an average 30-day rehospitalization rate that increased with worsening (increasing) ADI, from 22% to 27%. The authors also suggest that neighborhood disadvantage displays a threshold effect, concluding that individuals can overcome the adversity of living in a deprived area up to a certain threshold of disadvantage. Beyond that point, individuals can no longer compensate for the high deprivation and are more susceptible to adverse outcomes.(11)

Dr. Kind later worked with Michigan authors Hu and Nerenz to explore ADI and hospital readmission risk using 2010 Medicare patient discharge and readmission data from Henry Ford Hospital in Detroit, MI. The authors questioned if Medicare's pay-for-performance reimbursement model treats safety net hospitals fairly, given their more deprived populations and higher predisposition to poor outcomes. The study found that community-level variables can influence health outcomes (like hospital readmissions) independent of patient-level characteristics. The relationship between ADI and readmission was not linear, though. Across lower levels of deprivation, there was no significant effect on admission rate; however, those in the top 5% of deprivation were 70% more likely to be readmitted than those at lower deprivation levels.(17) Similar to the "threshold effect" described in Dr. Kind's 2014 paper,(11) the authors of this study developed a "minimum necessity" theory, suggesting there may be a minimum threshold for support services available in a given neighborhood. If this threshold is met, readmission is less likely; if the minimum threshold is not met, readmission may be more likely, despite other mitigating factors. The authors argue that accurate, unbiased assessment of healthcare quality requires modification for confounding factors that influence quality measures but are not directly related to the quality of care provided. Risk-adjustment models and quality measures should factor in both patient-level and area-level variables.(17)

Johnson and colleagues studied the relationship between ADI and cardiac readmissions. They found that patients with heart failure who were in the highest ADI quintile (most deprived) had a 25% higher 1-year risk of readmission than those in the lowest ADI quintile (least deprived). Patients with myocardial infarction who were in the highest ADI quintile had more than twice the risk of readmission when compared to those in the lowest ADI quintile. Interestingly, risk of 1-year readmission in patients with atrial fibrillation had the opposite association with ADI, where those in the highest ADI quintile were *less* likely to be readmitted to the hospital within 1 year when compared to those in the lowest ADI quintile. Given the findings of the study, the authors advocate for identifying patient deprivation at the time of inpatient admission, such as assigning an area deprivation score to a patient, preferably within the electronic health record (EHR). With strategic resource allocation, those in the most deprived areas may experience fewer hospital readmissions within 1-year of discharge.(18)

Michaels, et al, hypothesized that using a deprivation score, such as the Distressed Communities Index (DCI) or the ADI, could help with surgical risk stratification, given the link between socioeconomic status and surgical outcomes.(19) The American College of Surgeons National Surgical Quality Improvement Program (ACS NSQIP) Risk Calculator uses the planned procedure and 19 patient-level variables to risk stratify patients having surgery. However, the calculator does not include any socioeconomic factors and primarily focuses on health status/comorbidities.(20) The authors found that with each increase in ADI quartile, there was an 11% higher surgical complication risk. Conversely, the DCI was not found to be predictive of morbidity across the population. The authors believe that adding the ADI to surgical risk-stratification methods would allow for more accurate risk assessments and a means of prioritizing healthcare resources and community support in the most deprived/highest risk locales.(19)

Zuelsdorff and colleagues studied ADI in the context of Alzheimer's disease risk assessment. When cognitively unimpaired patients with parental history of Alzheimer's disease underwent cognition testing, those living in the 20% most disadvantaged areas (highest ADI) recalled fewer words on verbal learning and delayed recall tests and took longer to complete executive function tasks when compared with the least disadvantaged areas (bottom 80% of ADI). No association between ADI and processing speed was observed. Given that the test results showed poorer cognitive function amongst those with the 20% highest ADI, the authors suggest that using neighborhood deprivation information may be a helpful marker for research that aims to help those with a high risk for cognitive dysfunction, such as those with a parental history of Alzheimer's disease. Focusing on at-risk patients residing in neighborhoods with higher deprivation may help researchers identify risk factors for cognitive decline/vulnerability to Alzheimer's disease.(21)

Among chronic diseases, cancer is one that attracts much attention when it comes to defining risk factors. Hufnagel and team specifically looked at ADI and its potential effect on ovarian cancer survival. Their study identified patients at Vanderbilt University Medical Center who were diagnosed with primary ovarian cancer from 1994 to 2004 and linked them to 2015 (v2) state and national ADI values based on the patients' addresses at the time of diagnosis.

When overall survival was adjusted for patient characteristics—such as age at diagnosis, race, stage, histologic subtype, and grade—they found that patients with a higher than median state ADI (most deprived) had a roughly 40% higher risk of death than those with a lower state ADI (least deprived). When the data was examined in a continuous manner, they found that each decile increase in state ADI was associated with a 10% increase in the risk of death. The authors recommend that future studies explore opportunities for social intervention given the stress of living in areas of high deprivation and the possible physiologic effects that lead to inequalities in cancer survival.(22)

Other researchers have focused on the psychological impact of cancer. Rosenzweig and colleagues studied the association between ADI and patient-reported outcomes in terminally ill cancer patients aged 21 years or older with metastatic solid tumors and found an independent positive association between anxiety symptoms and ADI. In other words, among patients who know they will not survive their disease, those in less disadvantaged areas reported having less anxiety than those living in more disadvantaged areas. The authors argue there is utility in looking at outcomes other than survival in cancer patients, and further studies may help identify tangible interventions to improve cancer patients' quality of life.(23)

More recently, a group from Johns Hopkins studied the relationship between ADI and COVID-19 infection prevalence in rural and urban populations. They classified 3,142 counties and parishes across the United States as either urban (county has at least 50,000 residents and an urban nucleus of at least 1,000 people per square mile or is a surrounding county with at least 500 people per square mile) or rural (does not meet the previous criteria) and used their own CDC-derived COVID-19 tracking information spanning January 22, 2020, to August 20, 2020. Because the CDC COVID-19 data was only available at the county/parish level, they created their own county-level ADI using Dr. Singh's method and the 2018 5-year ACS data. They found that COVID-19 prevalence was higher in urban counties, but that rural COVID-19 prevalence was more correlated to their national ADI rank than urban COVID-19 prevalence. With each unit increase in ADI, urban counties saw a 0.9% increase in COVID-19 prevalence, while rural counties saw a 2% increase in COVID-19 prevalence. The authors believe the rural health disparity led to exacerbation of the pandemic, and that interventions during a pandemic should address the geosocial factors that underlie the spread of infection.(24)

Multiple studies have been published on the relationship of diabetes to ADI. Hu and colleagues studied obesity and diabetes in Gulf Coast residents using Dr. Kind's 2013 ADI dataset. They found a positive association between area deprivation and diagnosis of diabetes, and the adjusted prevalence ratio showed a statistically higher rate of obesity when comparing individuals in the second, third, and fourth ADI quartiles (top three most deprived quartiles) with individuals in the 1st ADI quartile (least deprived quartile).(25) Kurani and associates studied the relationship of diabetes care quality and ADI. The study used Minnesota's D5 composite quality metric of optimal diabetes care to evaluate diabetes care quality, to include hemoglobin A1c less than 8.0%; blood pressure less than 140/90 mmHg; statin use appropriate for the patient's age, low-density lipoprotein cholesterol (LDL-C) level, and history of cardiovascular disease; aspirin use that is appropriate in the setting of ischemic vascular disease, and abstinence from tobacco use. They found that those who met the D5 metric, defined as meeting all five of the criteria, had a slightly higher average number of clinician visits compared with those who did not meet the D5 metric and were more likely to live in urban areas rather than rural areas. As ADI quintile increased, the probability of meeting the D5 metric decreased, and the individuals in quintile five (highest deprivation) were 28% less likely to meet the metric than the individuals in quintile one (least deprived). Interestingly, the individuals in ADI quintile five were significantly more likely to meet the lipid control criterion than those in ADI quintile one.(26)

Kurani and colleagues also published a study comparing ADI with hypo- and hyperglycemic crises in diabetic adults. They calculated ADI at the county-level for all 3,142 US counties/parishes, since the health data they used from the OptumLabs Data Warehouse (OLDW), a large national database, was only available at the county level. They found that individuals living in the most deprived ADI quintile (quintile 5) had a 41% higher risk of severe hypoglycemia than individuals living in the least deprived ADI quintile (quintile 1), and this finding was significant in all age groups, males, and females. Individuals in ADI quintile 5 had a 12% higher risk of diabetic ketoacidosis and hyperosmolar hyperglycemic state than those living in ADI quintile 1, but the difference between the two quintiles was only statistically significant in the 18-44 age group and in women.(27)

In alignment with numerous other publications, Kurani and colleagues noted that "The neighborhoods in which people live inform the structural conditions that ultimately shape their health, independent of their individual-level characteristics."(27) While the validation studies above use different versions of area deprivation indexes and different breakdowns in ADI to compare most deprived to least deprived individuals, the overarching theme is clear – health outcomes are more strongly impacted by neighborhood/area deprivation factors, with individual factors having less of an effect on individual outcomes.

ADI: Best Tool Available

Authors Powell, Sheehy, and Kind authored a Health Affairs article arguing their belief that using ADI is the best way to advance health equity. They argue that, given the varying levels of disadvantage across the United States, resources should be "targeted to areas of greatest need."(28) In 2022, the Centers for Medicare & Medicaid Services (CMS) announced that they would use national ADI percentile, plus 25 points for Medicare/Medicaid dual eligibility (full or partial), to adjust ACO Reach benchmarks as follows: increase of $30 per beneficiary per month for those in the 91-100 range and decrease of $6 per beneficiary per month for those in the 1-50 range. CMS acknowledges that the health equity benchmark adjustment, or HEBA, may need future evaluation and revision.(29) Though some have made "face validity" claims against ADI, which are susceptible to bias and conflict of interest, Powell and colleagues argue that re-weighting the ADI would undermine its strength and scientific rigor, given that the original methodology has been validated by hundreds of independent health research studies. With a tool like ADI, scholars can weigh in with opinions on whether the tool is correct, but only large numbers of independent scientific validation can prove whether or not the ADI serves its intended function, which is to determine neighborhood-level disadvantage. The authors believe that the ADI is currently the "most validated scientific tool for US neighborhood level disadvantage."(28)

ADI: Flawed and Needing Revision

Despite an abundance of literature supporting the use of the ADI, some have been outspoken about its weaknesses. Using ADI data primarily from the State of New York, Hannan and colleagues argue that the ADI has an overemphasis on home value. Their calculations showed a very strong correlation with median home value decile and overall ADI decile (R=0.98) in certain regions of New York State. They found that in the downstate region (including boroughs of New York City), areas with high median home values that showed high levels of deprivation in most other ADI variables were rated as having an overall low amount of deprivation according to the overall ADI score. They also found the opposite to be true: areas with low home values, where most other ADI values showed low deprivation, were given high ADI scores, indicating high overall deprivation. There are four ADI variables expressed in dollars (median home value, median family income, median monthly mortgage, and median gross rent), while the other 13 ADI variables are expressed in proportions from 0.0 to 10.0. Hannan and colleagues believe the ADI could be improved by standardizing the variables expressed in dollars before calculating the overall ADI, arguing that this would address regional differences and make the ADI more relevant across regions of the country. The current ADI methodology may lead to inadequate resources being dedicated to deprived neighborhoods with high housing prices, while the improvements suggested by Hannan and colleagues would minimize the ADI's variance based on the housing market in various locations, which does not always correlate to level of socioeconomic disadvantage.(30)

Stephen Petterson performed a study comparing a standardized version of ADI with the ADI in its current form. He found that with the current ADI methodology, home value and median income, two of the 17 variables used to calculate the ADI, account for all the variation in scores (> 99%). In his standardized version of the ADI, home value and median income accounted for only 72% of the variation in ADI. Failing to standardize the home value and median income also means that the weighting of these variables differs widely across block groups: the higher the dollar values, the greater the weighting in overall ADI calculation. Petterson is doubtful that the ADI is the best tool to use for allocating resources based on calculated deprivation, because very disadvantaged areas of large cities would not be considered deprived enough to qualify for government resources and programs.(31)

This Study

Though many validation studies have been published comparing ADI with various health measures and outcomes, studies comparing different versions of the ADI are not readily found in the literature. Beginning with the 2020 version of the ADI, the newly re-drawn census block groups entered use, and the “no household phone” measure was substituted with “no household internet.” These changes were thought to make the 2020 and later ADI versions incomparable with the earlier ADI versions.(14)

The primary objective of this study is to compare Louisiana state and national ADI values from two different years (2015 and 2021) with both acute (COVID-19) and chronic (obesity and diabetes) health measures to determine whether the pre- or post-2020 ADI better correlates with known acute and chronic health outcomes in patients living in Louisiana. We hypothesize that, given the changes implemented starting with the 2020 version of the ADI, and the proximity of the 2021 version of the ADI to our study period, the 2021 ADI will better correlate with the acute health outcomes (COVID related). We also hypothesize that the 2015 ADI will better correlate with Louisiana patients’ health measures for chronic diseases, because deprivation experienced over longer periods of time may contribute to the development of chronic diseases. In both cases, we expect the national ADI to show stronger correlations, given the higher level of granularity (1 to 100 percentiles, versus state ADI’s 1 to 10 deciles). We also expect to find worse health measures in areas of higher deprivation, as has generally been the case in previous ADI validation studies(17-19, 21, 22, 24, 26, 27).

Given the wide geographic footprint of the Ochsner Health system in Louisiana, which treats a large patient population that includes residents of every parish in the state, we chose to test our hypothesis by conducting a retrospective analysis of the Ochsner patient database. The findings of this study may be able to inform future health policy and resource allocation in the State of Louisiana. Additionally, if the study shows a close similarity between the 2015 and 2021 ADI versions, researchers and skeptics may gain more confidence in the newer version of the ADI and support its ongoing and future use.

Methods

Patient Population

Ochsner Health is a geographically diverse not-for-profit healthcare system with headquarters in Louisiana. The Ochsner Health system is comprised of 45 facilities and over 6 million unique patient lives across four states in the Gulf South. Ochsner Health operates as a PCORnet (The National Patient-Centered Clinical Research Network) data node as part of REACHnet (Research Action for Health Network).(32, 33) The PCORnet common data model (CDM) is designed for easier querying for research and analysis.(34, 35) We queried the entire Ochsner PCORnet CDM to gather deidentified health data that originated in our EHR. Patients were included if they had an encounter within the Ochsner Health system between September 30, 2021, and September 29, 2023 (the study period); they were 18 years or older as of September 30, 2021; and their most recent address was in Louisiana. Patients were excluded if a geographic entity code (GEOID) was not able to be assigned using their given address, or if they did not have a matching ADI for their GEOID.

Demographic Information

Demographic information was queried on the patient population to include age, sex, race, and ethnicity.

Geocoding and ADI Assignment

Using each patient's most recent address, geocoding was performed in Python using GeoPandas spatial merge (36) and TIGER/Line shapefiles available from Census.gov (37) to generate GEOIDs to the census block group level. Using the GEOID, patients were assigned their corresponding Louisiana state and national 2015 (2015 ADI v3.0) (38) and 2021 (2021 ADI v4.0) (39) ADI values, which were downloaded from https://www.neighborhoodatlas.medicine.wisc.edu/.

Chronic Health Measures

Obesity and Diabetes Mellitus (DM) were the two chronic health conditions that were selected for analysis.

To evaluate DM as a chronic condition in our patient population, most recent Hemoglobin A1c (HbA1c) values were collected from all patients, regardless of diabetes diagnosis status. The number of DM encounters, defined as any encounter containing DM as an encounter diagnosis, was also obtained. The SNOMED concept hierarchy for DM, #73211009, was used to identify DM encounter diagnoses for inclusion, and the SNOMED concept hierarchy for gestational DM, #11687002, was used to exclude encounter diagnoses related to gestational diabetes.(40) Those with no HbA1c lab value were given a HbA1c value of "Null" and were excluded from all HbA1c-related analyses. Those with zero DM encounters were recorded as "Null" and excluded from all DM encounter-related analyses.

To further evaluate obesity as a chronic condition in our patient population, most recent Body Mass Index (BMI) values, calculated from the encounter weight and height recorded in the EHR, were collected from all patients regardless of weight classification. The number of obesity encounters, defined as any encounter containing obesity as an encounter diagnosis, was also obtained. The SNOMED concept hierarchy for obesity, #414916001, was used to identify obesity encounter diagnoses for inclusion.(40) Those with no recorded BMI during the study period were given a BMI value of “Null” and excluded from all BMI-related analyses. Those with zero obesity encounters were recorded as “Null” and excluded from all obesity encounter-related analyses. All chronic health measures were collected from the study period only.

Acute Health Measures

To assess the deprivation impact of acute health conditions, COVID-19 (COVID) vaccination and hospitalization rates were analyzed. The quantity of COVID vaccination injections a patient had received was recorded, including those available in the state’s vaccine registry (Louisiana Immunization Network, or LINKS),(41) and those patients with 1 or more vaccinations were deemed to be vaccinated for COVID. COVID inpatient encounters were also recorded. An encounter was deemed to be COVID-related if the patient tested positive for COVID-19 within seven days prior to the admission (at any organizational testing location) or within three days after the encounter admission date. All acute health measures were collected from the study period only.

Analysis and Statistics

We present basic demography and patient population characteristics using 2021 national ADI values in tabular form, separated by ADI quintile, with mean and standard deviation values where applicable. The 2021 national ADI Quintiles are defined as follows: Q1 corresponds to ADI percentiles 1 to 20; Q2 corresponds to ADI percentiles 21 to 40; Q3 corresponds to ADI percentiles 41 to 60; Q4 corresponds to ADI percentiles 61 to 80; and Q5 corresponds to ADI percentiles 81 to 100.

Histograms were created for data visualization and determination of data distribution. Scatter plots of ADI values were created to compare Louisiana state values with national values. The average change in individual patients' ADI from 2015 to 2021 was calculated for both Louisiana state and national ADI values. The absolute value of the average change indicates the overall magnitude of change, while the directional average change indicates whether the ADI became higher (indicating higher relative deprivation), more negative (indicating lower relative deprivation), or stayed the same from 2015 to 2021. Pearson correlations were performed to assess relationships between ADI values and the chronic and acute health measures. The Pearson correlation r-to-z transformation was calculated to determine if the Pearson correlation coefficients were statistically different when comparing the correlations for 2015 and 2021 ADI values.(42) The Welch two sample t-test was performed to compare the means of the quintile 1 (Q1) and quintile 5 (Q5) BMI, HbA1c, DM encounters, and obesity encounters, to determine if the Q1 and Q5 values were statistically significantly different. Odds ratios were calculated for COVID vaccination rates and COVID inpatient stays to determine if the Q1 and Q5 values were statistically significantly different.(43)

All statistical analyses (with the exception of the Pearson correlation r-to-z transformation and the odds ratios) and figure generation were carried out using R 4.4.0 (44) in RStudio version 2024.01.1+748 for MacOS. Due to the large study cohort and multiple comparisons, an alpha value of < 0.001 was selected to define statistical significance. The study was approved by the Louisiana State University Health Sciences Center Shreveport Institutional Review Board, which waived the informed consent requirement due to the minimal risk of the study.

Results

Our database contained 3,176,168 patients in the PCORI CDM format, of which 3,175,637 were able to be geocoded to the census block group level. Of this population, 2,663,485 live in Louisiana (according to the most recent address on file), and 2,204,589 were 18 or older as of 9/30/2021. A total of 2,151,049 patients were able to be matched with their ADIs, and this number represents the base cohort for our study (see Figure 5).

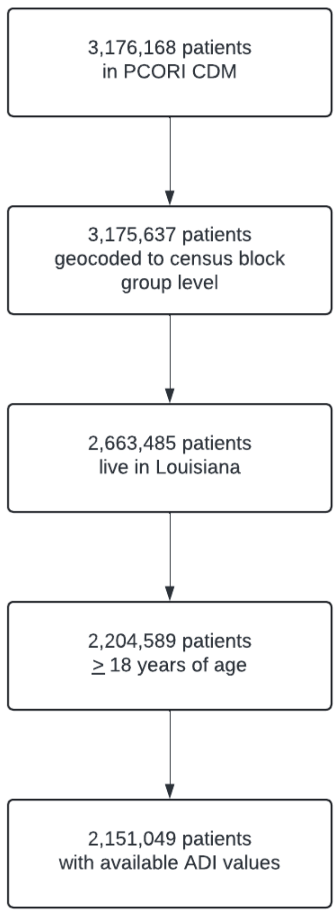

Figure 5

Histograms and scatter plots are shown below.

Figure 6. Distribution of BMI

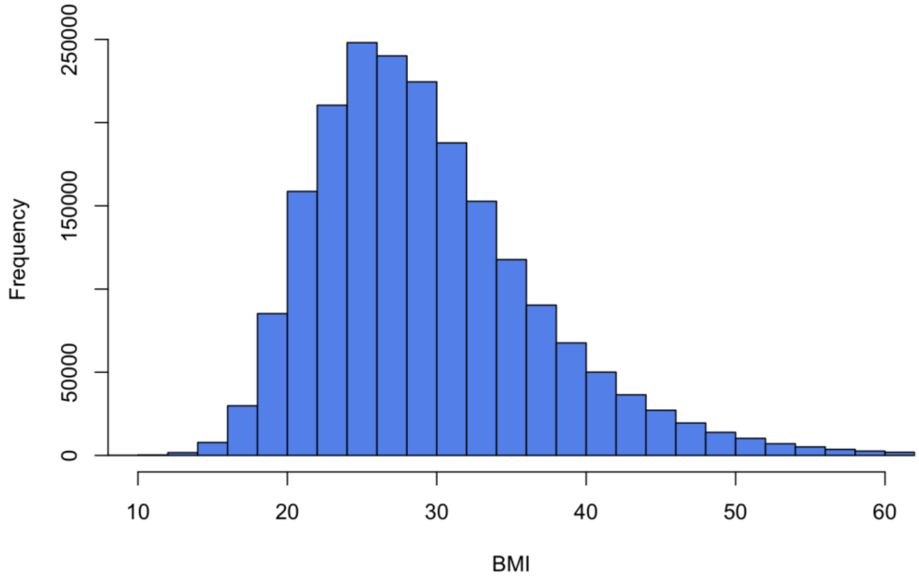

Figure 7. Distribution of HbA1c

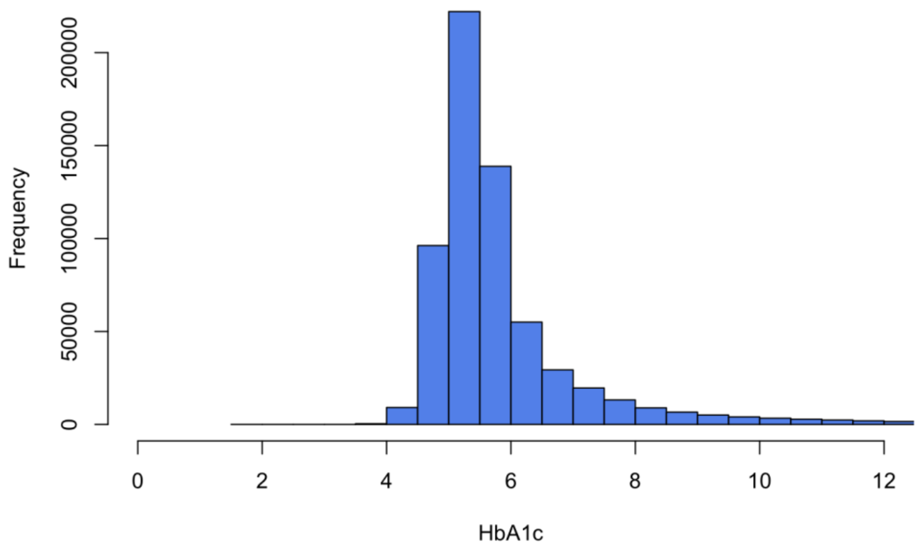

Figure 8. Distribution of 2021 National ADI

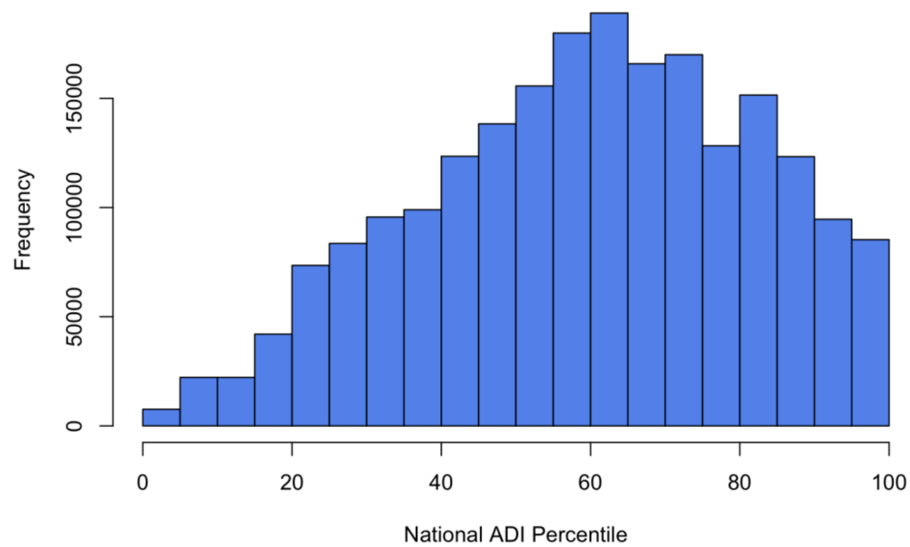

Figure 9. Distribution of 2021 Louisiana State ADI

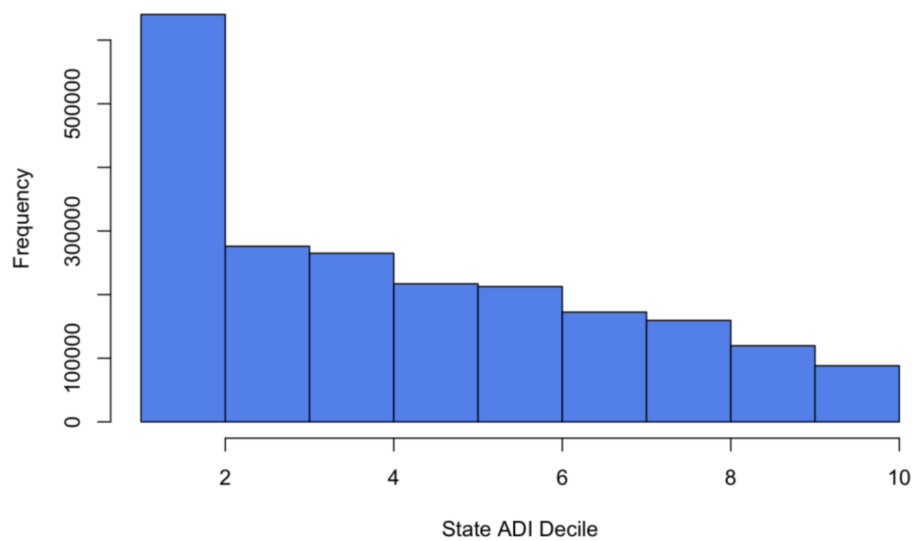

Figure 10. 2015 State vs National ADI

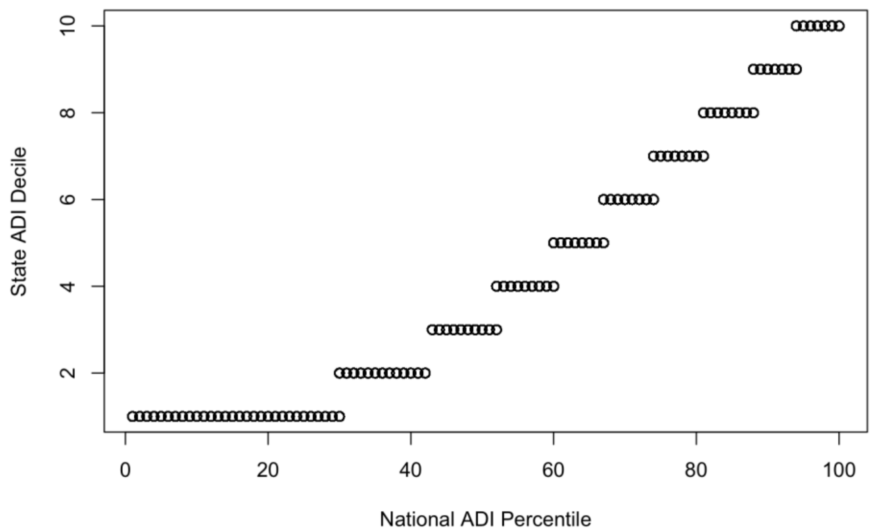

Figure 11. 2021 State vs National ADI

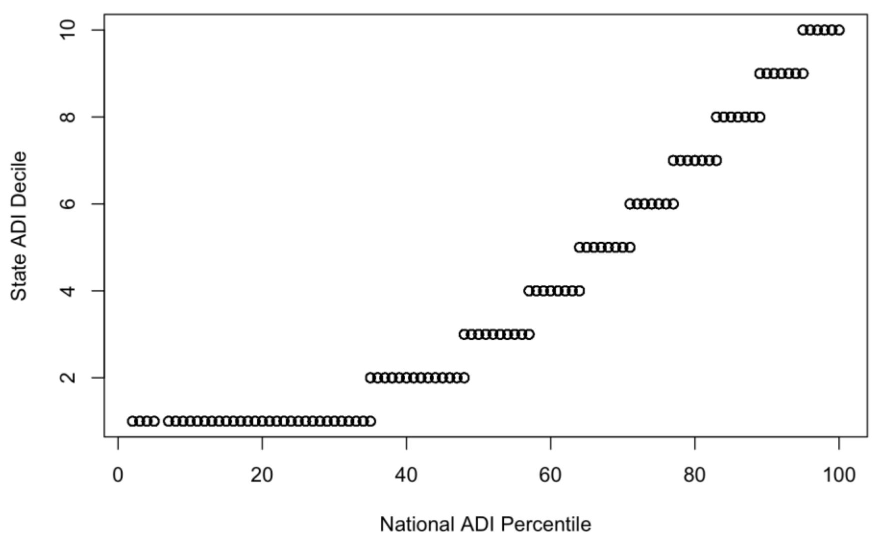

Figure 8 shows the distribution of national ADI percentile of our study population. The distribution is slightly skewed, with a higher proportion of the study population residing in areas of greater deprivation relative to the overall U.S. population. The mean 2021 national ADI percentile for the study cohort is 60.0. Figure 9 shows the distribution of Louisiana state ADI decile of our study population. This distribution is also skewed, but toward lesser deprivation, with a greater proportion of the study population residing in the lower state ADI deciles than the higher state ADI deciles.

The scatter plots in Figures 10 and 11 show the relationship between the Louisiana state ADI values and the national ADI values. In 2015 (Figure 10), the state decile 1 ADI values span national ADI values up to approximately 30%, and some residents in state decile 3 surpass the 50% national ADI value. Likewise, the 2021 values (Figure 11) show that state decile 1 ADI values span national ADI values up to approximately 35%, and some residents in state decile 3 approach the 60% national ADI value.

The 2015 and 2021 national ADI values were compared, and the total average change in national ADI value per patient from 2015 to 2021 was found to be 10.51 percentiles (absolute value). The total directional change from 2015 to 2021 was 4.92 percentiles. The 2015 and 2021 state ADI values were compared, and the total average change in state ADI value per patient from 2015 to 2021 was found to be 1.15 deciles (absolute value). The total directional change from 2015 to 2021 was 0.21 deciles.

The study population characteristics using the 2021 national ADI values are shown in Table 2.

Notably, the proportion of patients in Q1 in our study cohort (4.4%) is substantially lower than the proportion of patients in Q2 through Q5 in our study cohort (16.4% to 30.4%). Additionally, the proportion of black patients in our study increased with increasing ADI quintile, comprising only 8.66% of the patients in Q1 but increasing to 51.56% of the patients in Q5. The proportion of white patients decreased with increasing ADI quintile, going from 83.77% of our study population in Q1 down to 42.72% of our study population in Q5. The proportion of females in our study population remained fairly stable across ADI quintiles, comprising between

55.26% and 57.04% of the patients in Q1 to Q5. Likewise, the proportion of non-Hispanic or Latino/a patients in our study remained stable across ADI quintiles, ranging from 90.78% to 92.17%.

The average Hemoglobin A1c (HbA1c) increased as the 2021 national ADI quintile increased, with an increase in HbA1c when comparing Q1 to Q5 (t-test shows mean difference of 0.62, 95% CI 0.61 to 0.64, $p << 0.001$). With the exception of Q2, the average number of DM encounters decreased with increasing ADI quintile, with a decrease in DM encounters when comparing Q1 to Q5 (t-test shows mean difference of 1.79, 95% CI -2.23 to -1.34, $p << 0.001$). The average BMI increased as the ADI quintile increased, with an increase in BMI when comparing Q1 to Q5 (t-test shows mean difference of 3.87, 95% CI 3.83 to 3.92, $p << 0.001$). The number of obesity encounters per patient with at least 1 obesity encounter increased with increasing ADI quintile. There was an increase in obesity encounters when comparing Q1 to Q5 (t-test shows mean difference of 0.56, 95% CI 0.46 to 0.65, $p << 0.001$).

The COVID vaccination rate decreased with increasing 2021 national ADI quintile and was more than twice as high in the least deprived ADI quintile (Q1) as compared with the most deprived ADI quintile (Q5) (33.8% vs 16%, odds ratio 2.69, 95% CI 2.64 to 2.73, $p < 0.0001$). The overall trend in rate of COVID inpatient stay increased with increasing ADI quintile. The rate of COVID inpatient stays was significantly higher in Q5 as compared with Q1 (odds ratio 2.23, 95% CI 1.97 to 2.52, $p < 0.0001$).

Table 2. Characteristics of Study Population

	2021 National ADI Quintile				
	Q1	Q2	Q3	Q4	Q5
No. of patients (%)	94114 (4.4)	351710 (16.4)	597328 (27.8)	653170 (30.4)	454727 (21.1)
Age in years, mean (SD)	50.86 (20.0)	51.41 (20.0)	50.60 (19.8)	50.46 (19.7)	50.80 (19.5)
Sex (n, %)					
Female	52006 (55.26)	195763 (55.66)	335130 (56.10)	367593 (56.28)	259379 (57.04)
Male	42095 (44.73)	155897 (44.33)	262086 (43.88)	285460 (43.70)	195233 (42.93)
Other	13 (0.01)	50 (0.01)	112 (0.02)	117 (0.02)	115 (0.03)
Race (n, %)					
Black	8151 (8.66)	52990 (15.07)	135601 (22.70)	228794 (35.03)	234473 (51.56)
White	78843 (83.77)	274464 (78.04)	421687 (70.60)	381447 (58.40)	194282 (42.72)
Other	7120 (7.57)	24256 (6.90)	40040 (6.70)	42929 (6.57)	25972 (5.71)
Ethnicity					
Non-Hispanic or Latino/a	86051 (91.43)	323279 (91.92)	544798 (91.21)	592979 (90.78)	419124 (92.17)
Hispanic or Latino/a	3246 (3.45)	15121 (4.30)	32213 (5.39)	39336 (6.02)	21005 (4.62)
Other	4817 (5.12)	13310 (3.78)	20317 (3.40)	20855 (3.19)	14598 (3.21)
BMI, mean (SD)	26.60 (5.86)	28.10 (6.65)	29.33 (7.39)	29.97 (7.85)	30.47 (8.34)
HbA1c, mean (SD)	5.50 (0.91)	5.67 (1.07)	5.83 (1.26)	5.98 (1.40)	6.12 (1.53)
Obesity Encounters, mean (SD)	3.15 (3.0)	3.37 (3.5)	3.51 (3.7)	3.68 (3.9)	3.71 (4.0)
Diabetes Encounters, mean (SD)	13.46 (12.7)	13.79 (12.8)	13.36 (13.0)	12.82 (12.7)	11.67 (12.2)
COVID Vaccination, No. (rate per 100 patients)	31802 (33.8)	104184 (29.6)	135860 (22.7)	128197 (19.6)	72612 (16.0)
COVID Inpatient Stay, No. (rate per 100 patients)	278 (0.3)	1578 (0.4)	3207 (0.5)	4231 (0.6)	2979 (0.7)

Abbreviations: SD, standard deviation; BMI, body mass index; HbA1c, Hemoglobin A1c

The Pearson correlation coefficients are shown in Table 3. The health measures were correlated with 2015 national ADI, 2015 state ADI, 2021 national ADI, and 2021 state ADI values. All p values were << 0.001.

Table 3. Pearson Correlation Coefficients (r values*)					
Category	Health Measure	2015 National ADI	2015 State ADI	2021 National ADI	2021 State ADI
Chronic	BMI	0.1265	0.1142	0.1278	0.1146
	Obesity Encounters	0.0263	0.0196	0.0340	0.0305
	HbA1c	0.1288	0.1212	0.1330	0.1258
	Diabetes Encounters	-0.0658	-0.0700	-0.0602	-0.0637
Acute	COVID Vaccination	-0.1225	-0.1161	-0.1237	-0.1154
	COVID Inpatient Stay	0.0102	0.0087	0.0127	0.0114

**All p values << 0.001*

The results of the Fisher r-to-z Transformation are shown in Table 4. For each of the health measures, the correlations with the 2015 and 2021 national ADI values were compared; the correlations with the 2015 and 2021 state ADI values were compared; the correlations with the 2015 state and national ADI values were compared; and the correlations with the 2021 state and national ADI values were compared. The resulting two-tailed p values reflect the statistical significance (or lack thereof) of the difference in the Pearson correlation coefficients.

Table 4. Pearson Correlations: Fisher r-to-z Transformation (two-tailed p values)					
Category	Health Measure	2015 v 2021 National	2015 v. 2021 State	2015 State v. National	2021 State v. National
Chronic	BMI	0.1902	0.6892	0.0000*	0.0000*
	Obesity Encounters	0.0183	0.0008*	0.0394	0.2846
	HbA1c	0.0178	0.0096	0.0000*	0.0000*
	Diabetes Encounters	0.1074	0.0703	0.2263	0.3125
Acute	COVID Vaccination	0.2077	0.4593	0.0000*	0.0000*
	COVID Inpatient Stay	0.0096	0.0051	0.1188	0.1770

**p values < 0.001*

Discussion

This study shows that three out of six selected acute and chronic health measures (BMI, HbA1c, and COVID vaccination) are more highly correlated with the 2021 national ADI than with the 2021 Louisiana state ADI. The same three health measures are more highly correlated with the 2015 national ADI values than with the 2015 Louisiana state ADI values. The only other difference between the 2015 and 2021 versions is seen with obesity encounters, where the correlation with 2021 state ADI values is higher than the correlation with 2015 state ADI values (see Tables 3 and 4). This supports our hypothesis that national ADI values would correlate more highly with health measures than Louisiana state ADI values. The results of this study do not support the hypotheses that acute health measures would be more highly correlated with 2021 ADI values and that chronic health measures would be more highly correlated with 2015 ADI values.

Assessment of chronic health measures demonstrated increases in HbA1c and BMI with increasing ADI quintile, which is expected since we typically expect patients in areas of greater socioeconomic deprivation to have worse health measures(17-19, 21, 22, 24, 26, 27). Interestingly, the increase in obesity encounters with higher ADI quintiles is relatively small, such that there is only a 0.56 encounter difference between Q5 and Q1 and is likely not clinically relevant. However, the decrease in DM encounters with increasing ADI quintile is a bit more dramatic, with a statistically significant 1.79 difference in average DM encounter number in Q1 versus Q5 patients. While the differences in DM encounters is likely not clinically relevant, as the study period covered two years and this represents a difference of less than one DM encounter per year, this look at chronic disease outcomes may suggest that those with greater socioeconomic deprivation may face greater challenges in obtaining appropriate care. Though it is beyond the scope of this study, we speculate that people living in areas of deprivation may experience difficulties with transportation, inability to leave work for medical appointments (because they work multiple jobs or have jobs without access to dedicated medical leave), and/or suffer from lack of education or understanding around the importance of follow-up for chronic health conditions. Without additional insight into particular social and economic hardships faced by these communities, we believe it is fair to say that the data shows significant differences in access to medical care and, consequently, health outcomes, for chronic diseases such as obesity and DM between Q1 and Q5 patients.

Looking at acute disease, the negative correlation of COVID vaccination rate with ADI values, and the positive correlation of COVID inpatient stay rate with ADI values, is congruent with prior literature that shows COVID vaccinations decreased rates of inpatient admission related to COVID during the COVID-19 pandemic.(45) The decrease in COVID vaccination rate with increasing ADI quintile may be related to lack of availability of social services in areas of higher deprivation. Again, though it is beyond the scope of this study, we speculate that, with respect to national health emergencies like COVID, Q5 communities – which typically have more non-English speakers and under-educated residents – may experience more confusion and fear around vaccinations in general, and a lack of understanding (or even an inability to read public service announcements) about the benefits of the COVID vaccine. Further, Q5 communities likely have less access to vaccination sites, less access to education about preventative measures (such as handwashing and social distancing), and less access to early interventions for suspected COVID infections. The outcome of this study suggests that deficiencies in the social services available in areas of deprivation may account for the lower COVID vaccination rates and higher COVID hospitalization rates.

The overall study results suggest that changes in Dr. Kind's ADI from the 2015 version to the 2021 version have maintained or improved ability of the ADI to correlate with various health measures. Given the lack of published literature comparing different ADI versions, this is a novel study that shows the integrity of the ADI has been maintained, and validation studies using the pre-2020 ADI versions remain relevant, even though pre-2020 versions of the ADI are supposedly incomparable due to re-drawn census block groups and other changes incorporated as of the 2020 version of the ADI.(14)

Similar to other prior ADI validation studies,(11, 17, 23) our study shows weak linear correlations when comparing the health measures to the ADI over the entire continuum. However, when comparing the health measures of those in 2021 national ADI Q1 with those in 2021 national ADI Q5, statistically significant differences are found. BMI, number of obesity encounters, HbA1c, and COVID inpatient stay rate are all significantly higher in Q5 individuals than in Q1 individuals, while DM encounters and COVID vaccination rate are significantly lower in Q5 individuals than in Q1 individuals. These results are similar to other studies that used various ADI cutoffs to show that those in the highest ADI ranges (most deprived) have significantly different (worse) health measures and outcomes than those in lower ADI ranges (least deprived).(11, 17, 18, 21, 26, 27)

Another interesting observation is the difference in ADI values for our patient population in 2015 versus 2021. Because we used the last recorded patient address for geocoding and ADI matching purposes, the 2015 and 2021 ADI values were assigned based on a single address for each patient in the study. The scatterplots showing the Louisiana state ADI values versus national values (Figures 10 and 11) show that for a given state ADI decile, the range of national ADI percentiles is higher than average. If our study population had state deprivation values that matched the deprivation levels on a national level, those in Louisiana state decile 1 should have national ADI percentile values ranging from 1 to 10. This mismatch is even more pronounced for 2021 than for 2015. These observations are compatible with the calculated differences in ADI, which reveal a directional increase of 4.92

percentiles when comparing the 2021 national ADI values to the 2015 national ADI values in our patient population. According to the mean 2021 national ADI value of 60.0%, the Louisiana residents included in this study are more deprived than the average United States resident, and within the study population, residents of Louisiana have become approximately 5% more deprived from 2015 to 2021, when compared to all residents of the United States.

ADI research has not substantially addressed the temporal relationships between past and present neighborhood/area deprivation versus present/future health measures and outcomes. It is estimated that people move around 12 times in their lifetime, with 5 or 6 moves occurring during the ages of 18 to 45.(46) This study cannot adequately address the question of how differences in past deprivation affect someone now living in a less deprived area, or vice versa, since prior home addresses were not included for analysis.

Strengths of this study include large patient population representing almost half the inhabitants of the State of Louisiana,(47) and the analysis of both state and national ADI values from two ADI versions from two different years (2015 version 3.0 and 2021 version 4.0). The large, diverse study population makes it plausible to generalize the study results across the entire State of Louisiana. The analysis involving multiple ADI versions allows for their comparison and a possible mechanism to determine which version may be best for future decision-making.

Limitations of this study include failure to address skewed racial composition of our study population, potential nonresponse bias affecting ACS results and ADI derivation, the low 2021 national ADI Q1 population (only 4.4% of the patients in our study), relying on physician/provider coding for identification of obesity and DM encounters, not accounting for potential health measure confounders such as smoking status and alcohol use, and using a patient population from a single healthcare system which might be inaccessible to some Louisiana residents based on insurance or other reasons.

Race is notably absent from the ADI, as originally discussed in Dr. Singh's ADI origin paper where he noted there was no statistically significant relationship between race and area deprivation.(3) This study was not designed to address differences in demographics among ADI quintiles. However, evidence exists that racial disparities in health outcomes exist in certain patient populations where ADI does not explain the disparities.(48) The racial composition of our study cohort trends toward higher concentration of black patients as the ADI quintile increases from Q1 to Q5. Future studies may be strengthened by independently examining the effect of racial composition on health outcomes.

ACS nonresponse bias may affect ACS results, which would in turn affect ADI values. If a census block group only has a small number of respondents for a given year or multi-year stretch, the paucity of responses may lead to bias in the deprivation level assigned to the census block group. This is an issue Dr. Kind's team has tried to address,(14) but evidence of the efficacy of their methods is not easily found in the literature.

The low 2021 national ADI Q1 population in this study (4.4%) may not be representative of the entire Louisiana population with national ADI percentiles of 1 to 20. Our study cohort was entirely comprised of Ochsner Health system patients, and due to the retrospective nature of the study, we were not able to institute measures to more equally represent 2021 national ADI Q1 in this study. Therefore, the statistically significant relationships between Q1 and Q5 may not be generalizable to the entire Louisiana population.

We ultimately decided to rely on coding for identification of obesity and DM encounters, so those with obesity and DM who had encounters that were not correctly or completely coded would have been left out of consideration for this study. Counting all patient encounters since diagnosis, either coded or objectively shown with lab values, BMI, etc., may be a better approach for future studies.

Without identifying and controlling for potential confounders, we cannot make conclusive statements of causality in the relationships we have identified between ADI and health outcomes in this study. However, the analysis we have presented aligns generally with existing published literature and has plausible social mechanisms that support deprivation, as measured by ADI, as a potential causal factor.

Lastly, the use of a dataset from a single healthcare system may lead to geographic and other biases that render the results of the study generalizable only to the patients of the healthcare system rather than the state population as a whole.

Additional studies should be done focusing on the most recent ADI version available. Additional metrics related to the health conditions examined in this study could be evaluated, and additional chronic conditions, such as cancer or Alzheimer’s disease, could be included for analysis. In addition, confounders affecting or related to the examined health measures could be identified and controlled for. State and/or national databases with health information may also be used in the future to supplement data from a single healthcare system.

Conclusion

This study shows correlations between health measures and ADI values when evaluating the entire continuum of ADI values and significant differences in health measures when comparing 2021 national ADI Q1 (least deprived) to Q5 (most deprived) patients. The 2021 national ADI values performed slightly better when compared to 2021 Louisiana state ADI values. While our study only examines a limited selection of health measures in relation to ADI, it is a meaningful addition to the ADI validation literature and suggests that the changes in the 2020 and post-2020 ADI versions are legitimate and have maintained the integrity of the ADI. The results of this study, in addition to the many other various ADI validation studies that have been published, support the use of ADI at the clinical level, to identify patients who are most in need of social interventions for health optimization, and at the state level, to inform policy and allow for the most efficacious resource allocation.

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