Health & Place 80 (2023) 102997

Contents lists available at ScienceDirect

Health and Place

journal homepage: www.elsevier.com/locate/healthplace

Measuring disadvantage: A systematic comparison of United States small-area disadvantage indices

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ARTICLE INFO

Keywords:
Disadvantage
Deprivation
Vulnerability
Mortality
Social capital

ABSTRACT

Extensive evidence demonstrates the effects of area-based disadvantage on a variety of life outcomes, such as increased mortality and low economic mobility. Despite these well-established patterns, disadvantage, often measured using composite indices, is inconsistently operationalized across studies. To address this issue, we systematically compared 5 U.S. disadvantage indices at the county-level on their relationships to 24 diverse life outcomes related to mortality, physical health, mental health, subjective well-being, and social capital from heterogeneous data sources. We further examined which domains of disadvantage are most important when creating these indices. Of the five indices examined, the Area Deprivation Index (ADI) and Child Opportunity Index 2.0 (COI) were most related to a diverse set of life outcomes, particularly physical health. Within each index, variables from the domains of education and employment were most important in relationships with life outcomes. Disadvantage indices are being used in real-world policy and resource allocation decisions; an index's generalizability across diverse life outcomes, and the domains of disadvantage which constitute the index, should be considered when guiding such decisions.

1. Introduction

Area-based disadvantage is considered to be when an area is characterized by adverse economic and social conditions (Wang et al., 2017). There is extensive literature establishing its relationship with life outcomes (such as health and mortality), vulnerability to disasters, and economic opportunity. For example, studies have shown that areas with higher levels of disadvantage suffer from increased all-cause mortality (Singh, 2003), lower economic mobility (Chetty et al., 2018), and greater impacts from outbreaks such as COVID-19 (Snyder and Parks, 2020). In addition, there are many studies demonstrating links between area-based disadvantage and certain health conditions such as chronic health conditions (Durfey et al., 2019) and hospital outcomes (Krager et al., 2021). Crucially, disadvantage indices are able to accurately identify areas experiencing disadvantage in order to effectively allocate resources and create policies and interventions to achieve equity. In the United States, indices are being used to help define payments for medically underserved beneficiaries (Bleser et al., 2022) and were used to determine allocation of treatment and vaccination during the COVID-19 pandemic (Srivastava et al., 2022; Kahn et al., 2020).

Area-based disadvantage is typically measured either using individual variables or composite indices, which combine multiple individual variables into a single summary score. Individual variables only measure a single aspect of disadvantage. For example, poverty is commonly used to measure an area's level of material disadvantage (Krieger et al., 1997). However, this does not consider other aspects of disadvantage that increase risk of adverse outcomes, since many social conditions influence outcomes in tandem and through multiple pathways (Link and Phelan, 1995). Thus, composite indices are used to capture many different aspects of deprivation, which can include area-level social, economic, and environmental characteristics (e.g., poor housing conditions or employment opportunities).

Disadvantage indices often utilize Census data available for the entire population. Researchers typically (1) select a range of *variables* to include in the index based on theoretical relevance (i.e., how disadvantage is operationalized), (2) group related variables together into

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https://doi.org/10.1016/j.healthplace.2023.102997
Received 14 November 2022; Received in revised form 2 February 2023; Accepted 21 February 2023
Available online 1 March 2023
1353-8292/Published by Elsevier Ltd.

categories called *domains* (such as housing and education), and then (3) run analyses such as factor or principal components analysis to create the final index (Allik et al., 2020). The final constructed indices summarize the data from a range of variables into a single score for each small-area, allowing one to capture the multidimensional aspects of disadvantage for more nuanced analyses (Allik et al., 2020). Additionally, these indices are easily interpretable and are often publicly available. As such, disadvantage indices are becoming more widely used (Tipirneni et al., 2022).

However, area-based disadvantage is not consistently operationalized with several competing definitions including vulnerability (Flanagan et al., 2011), deprivation (Singh, 2003), and opportunity (Acevedo-Garcia et al., 2020). As such, measurements of disadvantage vary across studies, even if those studies agree on the particular operationalization (e.g., deprivation; (Carstairs, 1995) . These inconsistencies lead to larger questions of how to best measure disadvantage and practical considerations, such as which index one should select for a particular research or policy question. Understanding such inconsistencies is important to determine the relationships between area-based disadvantage and life outcomes.

While empirical comparisons across various indices do exist, they are limited in scope and, e.g., only consider specific disease outcomes such as chronic disease (Lopez-De Fede et al., 2016) and COVID-19 (Tipirneni et al., 2022). Furthermore, it is unknown how data sources and methodologies affect downstream results. For example, it is unknown whether including variables from less common domains, particularly those from less convenient data sources than the Census and therefore are less likely to be included in a composite index, would better explain disadvantage. Additionally, indices are often constructed using varying methodologies, with different weightings of the variables they are composed of. It is also worth noting that some indices are primarily only used in one context: vulnerability indices have historically been used in the context of vulnerability to disasters (Bakkensen et al., 2017), and deprivation indices have historically been used in the context of health (Carstairs, 1995). There is limited work which compares these indices beyond the context in which they were originally developed, especially when the associated underlying disadvantage is highly similar. For example, a community's vulnerability to natural disasters (Flanagan et al., 2018) may be similar to its vulnerability to disease outbreaks (Dasgupta et al., 2020) or physical inactivity (An and Xiang, 2015).

In this study, we systematically compared five publicly available United States disadvantage indices in order to evaluate which indices generalize across contexts. We first compared the indices to each other, in order to measure similarity between the indices. Next, we compared their relationships with a diverse set of life outcomes from heterogeneous data sources across five categories: mortality; self-reported physical health, mental health, subjective well-being; and social capital. Finally, we identified which domains of variables are most important when constructing composite disadvantage indices. Since past studies have only examined specific disease contexts, our study contributes to reaching a consensus on which indices are best by comparing across a wide range of contexts. The findings of our study could help guide and inform the selection of indices by community organizations, policymakers, and researchers to better understand which indices to use and for which contexts.

2. Data and methods

To systematically compare indices, we proceeded in three steps. First, we examined index characteristics by qualitatively comparing indices on their domains and variables and calculating correlations between each of the indices. Next, we identified which indices are most related to a wide variety of relevant life outcomes from heterogeneous data sources (e.g., mortality from death certificates, self-reported health, and social media-based measures of social capital). Finally, we examine the contribution of each index variable (i.e., variables used to create the composite indices) to the indices' overall relationships with life outcomes.

2.1. Data

This is a secondary data analysis paper based on publicly available data sets. The predictors in this analysis are disadvantage index scores as well as a baseline single-variable measure of socioeconomic status. The outcomes in this analysis are mortality rates, physical health, mental health, subjective well-being, and social capital. Analyses take place at the U.S. county-level. When possible, the indices and outcomes were matched temporally and compared in the year 2015. A total of $N = 1101$ U.S. counties had sufficient data for all predictors and outcomes, representing approximately 88% of the U.S. population (see Supplement Fig. S1 for full exclusion criteria).

2.1.1. Disadvantage indices

We identified small-area level disadvantage indices whose national index score data were available for free public download ($n = 5$). Indices whose data were not publicly available, indices that were designed for one specific use case or health outcome (i.e. COVID-19 indices), and indices where health outcomes were variables within the index itself were not included in this analysis due to the potential for endogeneity bias. The following indices were included in the analysis: (1) the Area Deprivation Index (ADI; (Kind and Buckingham, 2018)) which is widely used in health research; (2) the Child Opportunity Index 2.0 (COI; (Acevedo-Garcia et al., 2020)) which measures opportunity for child development; (3) the Social Deprivation Index (SDI; (Butler et al., 2013)) traditionally used to predict healthcare access and need; (4) the Social Vulnerability Index (SVI; (Flanagan et al., 2011)) which is used to measure communities at-risk from disasters; and (5) another Social Vulnerability Index, the SoVI (Cutter et al., 2003), which measures vulnerability to disasters. See Supplement Table S1 for a summary of indices.

Area Deprivation Index (ADI; (Singh, 2003; Kind and Buckingham, 2018)): The Health Resources and Services Administration (HRSA) and University of Wisconsin's ADI uses 17 factor score weighted American Community Survey (ACS) variables from the U.S. Census that represent domains of income, education, employment, and housing quality to measure levels of disadvantage for small areas. The ADI is available at the Census Block Group level, which is a smaller spatial unit than a county. Thus, we computed county-level estimates by averaging across all block groups within a county.

Child Opportunity Index 2.0 (COI; (Acevedo-Garcia et al., 2020)): Brandeis University's COI uses 29 weighted variables from the ACS and other sources that represent education, health and environment, and social and economic domains, to measure opportunity for child development. The COI is available at the census tract level, which is a smaller spatial unit than a county. Thus, we computed county-level estimates by averaging across all census tracts within a county.

Social Deprivation Index (SDI; (Butler et al., 2013)): The Robert Graham Center's SDI uses 7 weighted ACS variables representing domains such as income and household characteristics to measure variations in socioeconomic disadvantage. The SDI is available at the county, census tract, Zip Code Tabulation Area (ZCTA), and Primary Care Service Area (PCSA) levels.

Social Vulnerability Index (SVI; (Flanagan et al., 2011)): The CDC's SVI uses 15 unweighted ACS variables categorized into 4 domains (socioeconomic status, household composition and disability, minority status and language, and housing type and transportation) to measure vulnerability to hazardous events. The SVI was compared in the year 2014 since data was unavailable for 2015. The SVI is available at the county and census tract levels.

Social Vulnerability Index (SoVI; (Cutter et al., 2003)): The University of South Carolina (USC)'s SoVI uses 29 weighted ACS variables grouped together by principal components analysis and measures vulnerability to environmental hazards. The SoVI was compared in the year 2014 since data was unavailable for 2015. The SoVI is available at the county level.

Baseline: To have a baseline of reference to compare the performance of the disadvantage indices to, we use a single county-level variable: the percentage of ninth-grade cohort that graduates in four years. This data was collected by EDFacts across 2014–2015 and distributed via the 2017 County Health Rankings (Remington et al., 2015).

2.1.2. Life outcomes

We included five categories of county-level life outcomes in the present data analysis: mortality, physical health, mental health, subjective well-being, and social capital. These were chosen due to the diversity in types of outcomes (for example, mortality, subjective measures of both health and psychological constructs, and behavioral measures of civic engagement) and heterogeneity in measurement (death certificates, self-reports, and social media estimates). Supplemental Table S2 contains the sources and years for all life outcomes; Supplement Table S3 contains all data sources, question, text, and scale ranges, while Supplemental Table S4 contains pairwise correlations between all life outcomes.

Mortality: We collected county-level age adjusted mortality rates from 2011 to 2015 from the Centers for Disease Control and Prevention (CDC) WONDER online database, calculated for all demographic groups (e.g., genders and race/ethnicity) combined. Mortality data were pulled for the top 10 causes of mortality in 2015 (Heron, 2017): (1) Diseases of the heart, (2) Malignant neoplasms, (3) Chronic lower respiratory diseases, (4) Accidents (unintentional injuries), (5) Cerebrovascular diseases, (6) Alzheimer's disease, (7) Diabetes mellitus, (8) Influenza and pneumonia, (9) Nephritis, nephrotic syndrome and nephrosis, (10) Intentional self-harm (suicide). Additionally, given its status as a public health emergency, we considered opioid poisoning mortality, which is a subset of both Accidents (unintentional injuries) and Intentional self-harm (suicide). See Supplement Table S5 for the International Classification of Diseases, Tenth Revision (ICD-10) codes used to pull the data from the multiple cause-of-death mortality files.

County-level self-reported physical health, mental health, and subjective well-being measures were obtained from the 2015 Behavioral Risk Factor Surveillance System (BRFSS) and Gallup-Sharecare Well-Being Index surveys. The BRFSS is an annual national health survey that collects data on health conditions and their risk factors in the United States (Centers for Disease Control and Prevention CDC, 2015). County-level aggregates of BRFSS data were collected from the 2017 County Health Rankings (Remington et al., 2015). The Gallup-Sharecare Well-Being Index is a large longitudinal survey that collects data on multiple aspects of well-being. Gallup data at the person-level was aggregated to create average measures at the county-level for the years 2009–2015. Following Jaidka et al. (2020), we only considered counties with at least 300 self-reports, which resulted in 1,661,107 self-reports that were averaged to N = 1101 counties.

Physical Health: We consider three measures: percent of fair or poor health, physically unhealthy days, and pain. From the BRFSS, percent of fair or poor health is calculated as the county-level percentage of respondents who reported their health as fair or poor, while physically unhealthy days is the average number of physically unhealthy days during the past 30 days. Pain, as measured by the average response to the question "did you experience physical pain yesterday", is from the Gallup-Sharecare Well-Being survey.

Mental Health: Our two measures included the average number of mentally unhealthy days during the past 30 days (as reported from the BRFSS) and depression, the percentage of participants who have been told by a physician or nurse that they have depression (as reported from the Gallup-Sharecare Well-Being survey).

Subjective Well-Being: All well-being measures were from the Gallup-Sharecare Well-Being survey. Following Ward et al. (2021), we operationalized positive affect as the average response to happiness, enjoyment, and laughter and negative affect as the average response to stress, worry, and sadness. The life satisfaction measures ask survey participants to evaluate their life as a whole, both today and five years from now.

Social Capital: County-level measures of social capital, the strength of social networks and communities (Chetty et al., 2022), were captured in three categories from a large national data set of 21 billion Facebook friendships: economic connectedness (two times the share of high-SES friends among low-SES individuals, averaged over all low-SES individuals in the county); cohesiveness, which is composed of clustering (the average fraction of an individual's friend pairs who are also friends with each other) and support ratio (the proportion of within-county friendships where the pair of friends share a third mutual friend within the same county); and civic engagement, measured using volunteering rate (the percentage of Facebook users who are members of a group which is predicted to be about 'volunteering' or 'activism' based on group title and other group characteristics) (Chetty et al., 2022). The data were obtained from Chetty et al.'s (2022) analysis of friendships on Facebook.

2.1.3. Variables of disadvantage indices

Given the number of indices and the large number of variables used to create each index, we proceed with the top two performing indices from the analysis identifying the top indices: ADI and COI. The individual variables of each index were identified from each index's methodology (Acevedo-Garcia et al., 2020; Kind et al., 2014). The ADI variables were collected from the U.S. Census while the COI variables were collected from the Child Opportunity Index 2.0 database (diversitydatakids.org, 2022). The full description of variables used to create the ADI and COI are included in Supplemental Table S6.

2.1.4. Data availability

All data used in this study, with the exception of the Gallup data (pain, depression, life satisfaction, and positive/negative emotions), is publicly available. We have publicly shared both the data and code used for the analysis at https://osf.io/7tbmp/?view_only=b28e3eca8f8e4b75afee6924489a5cdb.

2.2. Statistical analysis

All analyses were done using Python 3, using the PySal (Rey and Anselin, 2010) spatial analysis package.

2.2.1. Comparing index characteristics

First, we assigned each variable in each index to a subdomain (a group of similar variables) and domain (a group of similar subdomains), to qualitatively compare how each index operationalizes disadvantage. We also compute pairwise Pearson correlations between each index to assess how closely related each index is to the others.

2.2.2. Identifying top indices

When dealing with geographic data, one must account for spatial dependencies, i.e., the fact that counties close in space may have similar disadvantage and life outcomes. In such a context, statistical assumptions in a standard Ordinary Least Squares (OLS) regression are violated, namely, the independence of the model's residuals (Ebert et al., 2022). To account for spatial autocorrelation in our modeling, we ran a series of spatial regressions between each index (the independent variable) and each life outcome (the dependent variable). To do this, we use a spatial lag model to conduct the regression analysis; this model is used when a dependent variable in one county is directly influenced by a dependent variable in a neighboring county (Ward and Gleditsch, 2018). We included a spatially lagged version of the dependent variable (outcome) as a model covariate, specifically the average value of the dependent variable across all adjacent counties. This is analogous to autoregressive time-series models, which include a temporally-lagged variable. All variables are mean centered and normalized such that the resulting standard deviation is equal to 1. The regression equation is:

$$O_i = \beta_0 + \beta_1 I_j + \beta_2 L_i + \mu_{i,j},$$

where O_i is outcome i, I_j is index j, L_i is the spatially lagged version of outcome O_i, and $\mu_{i,\ j}$ is the error term. Note that two counties are considered adjacent if they touch in at least one point, which is operationalized by a Queen adjacency matrix, a commonly used spatial weight matrix (Ebert et al., 2022). This is a symmetric binary matrix where entries are 1 if two counties are adjacent and 0 otherwise.

We compared indices on their standardized beta coefficients β_1. To identify whether there were significant differences between indices, we conducted a boot-strapping test to identify differences between the standardized beta coefficients. That is, given a single life outcome and the two indices with the largest betas, we randomly selected counties (with replacement) and ran the above spatial regressions for the given index and outcome. We then subtracted the two standardized beta coefficients and repeated this process 10,000 times. A significant difference was noted if the 95% confidence intervals (of the differences in betas) did not overlap with 0.

2.2.3. Identifying top index subdomains

Finally, we identified the subdomains (i.e., groups of related variables) within an index which are most related to averages of each life outcome category (e.g., average mortality). For example, the variables median family income and income disparity (used to create the ADI) both fall under the income subdomain in the SES domain. A modified backward stepwise regression was performed to analyze which subdomains contributed most to the overall relationship with the life outcome for the top two performing indices (determined by highest overall average relationships with average life outcomes). The baseline model contained all variables (e.g., all variables used to create the COI) as independent variables and an average life outcome as the dependent variable (e.g., the average of all mortality variables). All variables were z-scored (mean centered and divided by the standard deviation) and life outcome averages were also computed via the average z-score of all subdomains within the life outcome category. We then performed a modified backward stepwise regression. Assuming k subdomains, at each step we (1) successively removed each subdomain (i.e., all variables with the subdomain), (2) computed the fit (Akaike information criteria; AIC; (Mazerolle, 2006)) of the resulting model using the k-1 variables, and (3) report the removed subdomain which resulted in the maximum AIC (i.e., the model with the lowest fit). The variables constituting the subdomain were then removed and the process repeated for the remaining k-1 subdomains. Thus, at each step we remove the subdomain which is most important when predicting the average life outcome. Finally, this entire process was repeated for each life outcome category and the top two performing indices.

3. Results

3.1. Comparing index characteristics

3.1.1. Qualitative comparison of index domains, subdomains, and variables

We compared the indices on the domains, subdomains, and variables they contained; all indices contained at least one variable that measured the subdomains of poverty, high school, employment status, and single parent households (Fig. 1). All indices except the COI contain a variable measuring households with no vehicle; instead, the COI measured excessive one-way commute duration and walkability (Supplemental Table S6). Besides single parent households, 3 of the 5 indices (ADI, COI, and SDI) did not contain explicit demographic information, such as age, gender, and race/ethnicity, while the SVI and the SoVI both contain several demographic variables.

Some indices contained variables that were unique to that specific index. The COI contains variables for early childhood, elementary, and college education in addition to high school, which is the case for all other indices. The COI is the only index that contains variables related to the physical environment such as access to healthy food and green space as well as toxic exposures. This is because the COI utilizes a number of data sources outside of the U.S. Census ACS 5-year estimates. The SoVI includes variables for specific racial/ethnic groups, specific employment categories (extractive industries, service industry, female labor force participation), and hospitals and nursing home residents per capita (Cutter et al., 2003).

3.1.2. Correlations between indices

Correlations between indices are shown in Fig. 1. The SVI and SDI were highly correlated with one another ($r = 0.92$), while the ADI and SDI were the least correlated with one another ($r = 0.42$). The ADI was most distinct from the other indices with an average Pearson correlation of 0.52; it was least related to the SDI, SoVI, and SVI, and it was most similar to the COI ($r = 0.69$). On the other extreme, the COI was most similar to the other indices with an average Pearson correlation of 0.75 and was most similar to the SVI ($r = 0.84$).

3.2. Identifying top indices

3.2.1. Mortality

On average the ADI (average $\beta = 0.29$) and COI (average $\beta = 0.29$) were the indices most related to mortality (Table 1). The indices were more related to mortality due to chronic diseases (including chronic lower respiratory diseases, cancer, heart diseases, and diabetes) rather than mortality due to injury or infectious diseases, and were less related to Alzheimer's disease and suicide mortality. The ADI was the index significantly most related ($p < 0.05$) to chronic lower respiratory diseases mortality (Table 1). The COI was the index significantly most related ($p < 0.05$) to diabetes and opioid mortality (Table 1). All indices

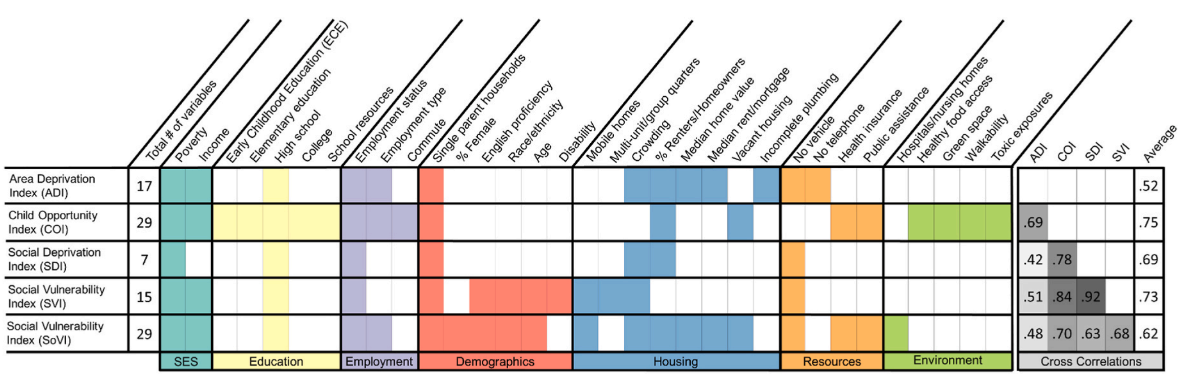

Fig. 1. Summary overview of each index. Subdomains (e.g., poverty) are listed at the top, while domains (e.g., education) are listed at the bottom. Highlighted blocks indicate that the index contains a variable that measures the above subdomain. Pairwise Pearson correlations computed for each index.

Table 1
Standardized beta coefficients between indices and outcomes. Red cells are positively correlated with disadvantage (i.e., are associated with more disadvantage) and green cells are negatively correlated with disadvantage (i.e., are associated with less disadvantage). White cells are not significant. All coefficients significant at $p < 0.05$ unless otherwise indicated (*ns*). Non-significant effect sizes are included in the averages, since excluding them could artificially increase the averages. Bolded numbers indicate the index which is statistically larger than all others (row-wise comparisons). See Supplemental Tables S7 through S12 for full results.

	Baseline	Disadvantage Indices				
	High School Graduation Rate	Area Deprivation Index (ADI)	Child Opportunity Index (COI)	Social Deprivation Index (SDI)	Social Vulnerability Index (SVI)	Social Vulnerability Index (SoVI)
Mortality						
Diseases of the heart	-.06	.43	.45	.30	.33	.20
Malignant neoplasms (cancer)	-.09	.47	.45	.28	.32	.21
Chronic lower respiratory diseases	*ns*	**.45**	.30	.13	.21	.08
Accidents (unintentional injuries)	-.08	.27	.31	.13	.21	.22
Opioid Poisonings[b]	-.07	.11	**.17**	.09	.11	.14
Cerebrovascular diseases	*ns*	.34	.34	.28	.29	.14
Alzheimer's disease	.06	.10	*ns*	*ns*	.06	.06
Diabetes mellitus	-.14	.40	**.44**	.37	.37	.27
Influenza and pneumonia	*ns*	.22	.25	.19	.20	.15
Nephritis, nephrotic syndrome and nephrosis	-.06	.31	.32	.26	.25	.13
Intentional self-harm (suicide)	*ns*	.07	.07	-.10	*ns*	.08
Absolute Average	*.06*	*.29*	*.29*	*.19*	*.25*	*.15*
Physical health						
Perc Fair or Poor Health	-.17	.44	.66	.66	.67	.47
Physically Unhealthy Days[a]	-.14	.44	.60	.52	**.55**	.43
Pain	*ns*	.41	**.45**	.21	.33	.27
Absolute Average	*.12*	*.43*	*.57*	*.46*	*.52*	*.39*
Mental health						
Mentally Unhealthy Days[a]	-.14	.35	.50	.42	.42	.35
Depression	-.09	.36	.37	.27	.31	.23
Absolute Average	*.12*	*.36*	*.44*	*.35*	*.37*	*.29*
Well-being						
Life Satisfaction today	.10	-.39	-.40	-.23	-.29	-.23
Life Satisfaction in 5 years	-.08	**-.29**	-.11	.11	*ns*	-.13
Positive Emotions	.09	-.29	**-.41**	-.33	-.35	-.25
Negative Emotions	-.06	.16	.24	**.28**	.25	.13
Absolute Average	*.08*	*.28*	*.29*	*.24*	*.23*	*.19*
Social Capital						
Economic Connectedness	.28	-.49	-.69	-.61	-.69	-.54
Cohesiveness: Clustering	.08	**.23**	.13	*ns*	.07	.10
Cohesiveness: Support Ratio	-.10	.36	.33	.21	.27	.30
Civic Engagement	.12	-.13	-.22	-.26	-.26	-.17
Absolute Average	*.15*	*.30*	*.34*	*.27*	*.32*	*.28*
Total Absolute Average	*.09*	*.31*	*.34*	*.25*	*.28*	*.22*

[a]: These outcomes are used to weight the COI, and therefore the COI is not considered when determining the highest related index.
[b]: Opioid poisonings data is only available for a subset of counties (n=862)

performed better than the baseline of high school graduation rate alone, which was not very related to mortality rates (average $\beta = 0.06$).

3.2.2. Physical health

The COI (average $\beta = 0.57$) and SVI (average $\beta = 0.52$) were the indices most related to physical health outcomes. The COI was the index significantly most related ($p < 0.05$) to pain ($\beta = 0.45$). Since the COI is ineligible for comparison for physically unhealthy days due to using this outcome in its weighting, the SVI was the remaining index significantly most related ($p < 0.05$) to physically unhealthy days ($\beta = 0.55$). The baseline was not very related to physical health (average $\beta = 0.08$).

3.2.3. Mental health

The ADI (average $\beta = 0.36$), COI (average $\beta = 0.44$), SDI (average $\beta = 0.35$), and SVI (average $\beta = 0.37$) all performed similarly for mental health. None of the indices were significantly more related to mental health outcomes than other indices. The baseline was not very related to mental health (average $\beta = 0.12$).

3.2.4. Subjective well-being

The ADI (average $\beta = 0.28$) and COI (average $\beta = 0.29$) were the indices most related to subjective well-being. All indices were negatively related to life satisfaction today, life satisfaction in 5 years, and positive emotions; however, the SDI was positively related with life satisfaction in 5 years. The ADI was the index significantly most related ($p < 0.05$) to life satisfaction in 5 years ($\beta = -0.29$). The COI was the index significantly most related ($p < 0.05$) to positive emotions ($\beta = -0.41$). The SDI was the index significantly most related ($p < 0.05$) to negative emotions (β = 0.28). The baseline was not very related to subjective well-being (average β = 0.12).

3.2.5. Social capital

On average, all indices performed similarly in relationships with social capital. The COI and SVI were very related to economic connectedness (β = −0.69). The COI and ADI were the indices most related to cohesiveness, including clustering and support ratio. The SDI and SVI were the indices most related to civic engagement (β = −0.26). While indices are negatively related to connectedness and civic engagement, they are positively related to cohesiveness.

In summary, the ADI and the COI were consistently the most associated with life outcomes (i.e., had the largest significant betas). Of the 24 life outcomes examined, 9 outcomes had a single index with a significantly (via bootstrapping test) larger beta than all other indices. Of these 9, the ADI was significantly highest in 3 outcomes (respiratory disease mortality, life satisfaction in 5 years, and clustering) and the COI was significantly highest in 4 outcomes (opioid poisoning mortality, diabetes mortality, pain, and positive emotions). The SDI and the SVI were each highest in a single outcome (negative emotions and physically unhealthy days, respectively). Full results are contained in Supplemental Tables S7 through S12.

3.3. Identifying top index subdomains

The COI and ADI were the top two performing indices and were selected for analysis of the contributions of each subdomain to the overall index's relationship with health. Fig. 2 shows the top 5 subdomains (used to construct both the ADI and COI) which were most associated with averages across each life outcome category (e.g., average mortality and average social capital). Full results are contained in Supplemental Tables S13 through S22.

For the ADI, high school (percent aged ≥25 years with greater than or equal to a high school diploma and percent aged ≥25 years with <9 years of education) was the subdomain that was the most related to county average mortality, average mental health, and average social capital. The ADI subdomain most related to average physical health was poverty (percent of families below the poverty level and percent of population below 150% of the poverty threshold). The ADI subdomain most related to subjective well-being was the percent of single-parent households with children <18 years of age.

For the COI, average mortality and average subjective well-being were most related to college, or the percent of adults ages 25 and over with a college degree or higher and percent 18-24 year-olds enrolled in college within 25-mile radius. Average physical health was most related to poverty, or the percent of individuals living in households with incomes below 100% of the federal poverty threshold. Average mental health was most related to receiving public assistance, or the percent of households receiving cash public assistance or Food Stamps/Supplemental Nutrition Assistance Program. Average social capital was most related to school resources, or the percent of students in elementary schools eligible for free or reduced-price lunches and percent teachers in their first and second year.

For both the ADI and COI, poverty was the most important subdomain for average physical health. Education subdomains, including high school, college, and school resources from the ADI and COI, were most important for average mortality and social capital.

Across each index and all life outcome categories, the domains of education and employment were more frequently in the top 5 subdomains than the other domains. Education and employment both appeared 13 times (26%) each and are equally represented in the top 5 most important subdomains. For the remaining domains, socioeconomic

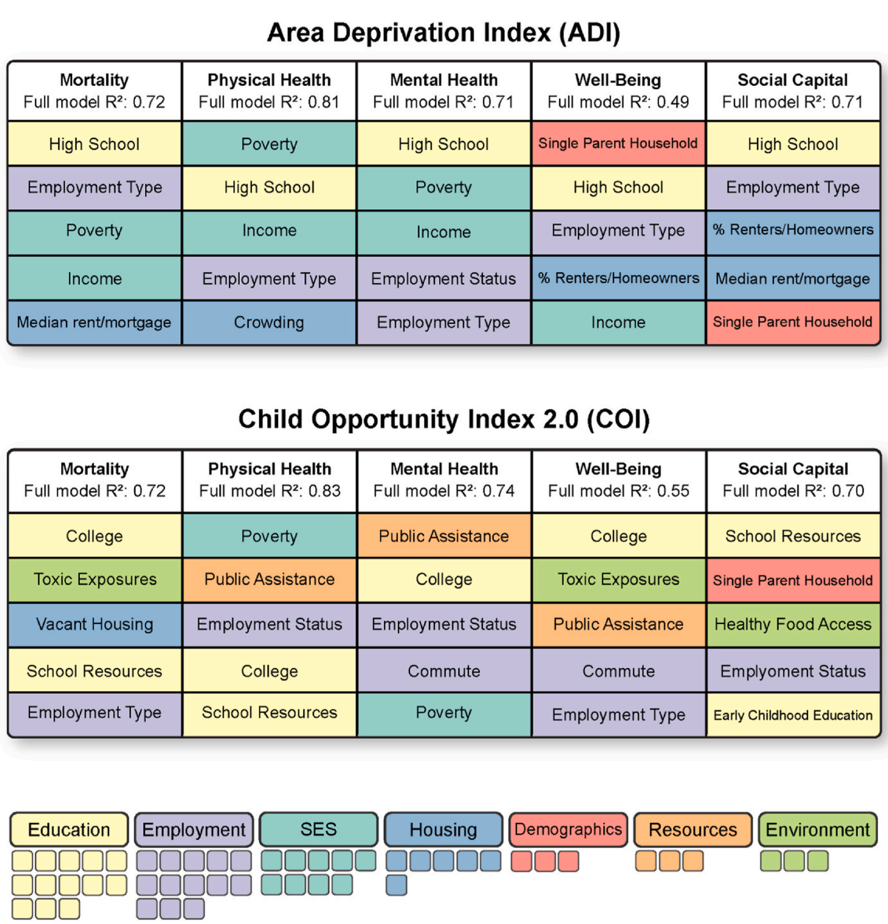

Fig. 2. The top 5 most related subdomains (in descending order) within the top two performing indices as identified through a backwards feature selection process. The Full Model R^2 is the proportion of variance explained before removing any subdomains. Cells are color coded according to their domain (e.g., education and housing). The squares at the bottom of the figure under each domain heading summarizes the number of occurrences when a domain appears in the top 5 predictors. For example, the Environment domain appears three times across the entire figure. Full results, including AIC values, are in Supplemental Tables S13 through S22.

status appeared 9 times (18%), housing 6 times (12%), and demographics, resources, and environment all 3 times (6%) each.

4. Discussion

In this study, we sought to identify which U.S. disadvantage indices are best to use by evaluating indices against a diverse set of life outcomes from heterogeneous data sources in order to see which indices generalize across a wide range of contexts. We systematically compared indices on their internal characteristics, compared relationships among indices with mortality, physical health, mental health, subjective well-being, and social capital, and explored which index variables were most related to outcomes. We found that the Area Deprivation Index (ADI) and Child Opportunity Index 2.0 (COI) were the best overall indices in this comparison, and education and employment variables (such as high school or college education and employment type or status) were the most important in driving overall index relationships with outcomes. Our findings support the consensus that the ADI and COI are parsimonious and efficient measures of disadvantage to predict a variety of physical, mental, social, and psychological health and well-being outcomes.

The ADI and COI showed the highest overall relationships with outcomes across mortality, physical health, mental health, well-being, and social capital categories. The ADI has been shown to be associated with many different health outcomes including chronic diseases (Durfey et al., 2019; Sheets et al., 2017, 2020), hospital and healthcare outcomes (Kind et al., 2014; Hu et al., 2018), and brain health and aging (Powell et al., 2020; Kind et al., 2017; Zuelsdorff et al., 2020), and the COI has been effectively utilized in the context of child outcomes such as childhood asthma (Gilbert, 2018; Grunwell et al., 2022) and child emergency department visits (Bettenhausen et al., 2021; Ramgopal et al., 2022). This study extends the ADI's validity beyond health to more upstream concepts including well-being and social capital, and demonstrates the COI's validity beyond childhood outcomes to adult and lifetime outcomes.

We found that the SVI and SDI performed moderately in comparison to the ADI and COI. The SVI and SDI were very strongly correlated with each other and performed similarly in relating to outcomes. This is most likely explained by the fact that six of out seven variables used to create the SDI are the same or very similar to variables used in the SVI, though we note that the SDI uses weighting while the SVI does not. Both the SDI and SVI performed inconsistently in this comparison; while more related to physical health (SVI) and negative emotions (SDI), both were less related, comparatively, in other contexts, making them unreliable across disciplines. Finally, we note that the SDI is inconsistently related to life satisfaction, as it negatively related to life satisfaction today yet positively related to life satisfaction in 5 years.

We found that the SoVI and single-variable baseline measure had the weakest relationships with outcomes overall in this comparison. Single-variable disadvantage measures similar to high school graduation rate have been demonstrated to underperform in comparison to disadvantage indices (Butler et al., 2013; Lian et al., 2016; Krieger et al., 2002). For example, one study determined that composite indices are better than single indicators due to representing broader dimensions of disadvantage (Lian et al., 2016). This study is among the first to evaluate the SoVI in the context of health, well-being, and social capital. We found that the SoVI contained many variables such as specific demographic groups and employment categories that were unique from other indices. However, these variables did not appear to strengthen its ability to relate to outcomes in this comparison, suggesting that those variables were not as relevant for these outcomes.

In our analysis, we found that indices that included race/ethnicity variables (SVI and SoVI) did not necessarily perform better than indices that did not (COI and ADI). Past literature has pointed out that it is important to distinguish between groups experiencing disadvantage and causal mechanisms behind disadvantage itself (Allik et al., 2020). Additionally, there is often debate over whether to consider race/-ethnicity when determining resource allocation (Schmidt et al., 2020). Indices may or may not be used in conjunction with race/ethnicity information, depending on political acceptability. However, some argue that considering race/ethnicity in resource allocation is vital and that the use of indices are "necessary, but not sufficient" to ensure health equity (Fressin et al., 2021). Thus, indices do not appear to need to include race/ethnicity variables to effectively measure or identify disadvantaged areas, but race/ethnicity may still be considered when determining resource allocation to aim to achieve equity.

There may be several explanations for why the ADI and COI performed better than other indices. In the case of the ADI, its effectiveness may be due to its spatial granularity at the census block-group level, the smallest geographic level of aggregation out of all indices compared. The COI contains variables like childhood education measures and environmental exposures that are unique from other indices due to its use of data sources outside the ACS (though these may be more labor intensive to obtain regularly over time). Additionally, it used external health and economic outcomes (Acevedo-Garcia et al., 2020) to weight the index variables rather than weights from a factor or principal components analysis. Both of these factors may explain the COI's strong performance in this comparison. Overall, differences in weighting and data sources in index construction appeared to contribute most to the differences observed in index performance in this comparison.

Overall, the small-area disadvantage indices were very related to physical health and are moderately related to mortality, mental health, well-being, and social capital, which is generally what has been pointed to in the literature. Income deprivation has been found to be associated with self-reported poor health (Subramanyam et al., 2009), which supports the strong relationship between disadvantage indices and self-reported physical health in this comparison. Mortality that is typically caused by chronic exposures over the lifetime such as heart disease, cancer, chronic lower respiratory diseases, and diabetes were more related to disadvantage indices than mortality typically due to one-time exposures or incidents such as influenza or suicide. Though we did not observe a relationship between indices and Alzheimer's disease mortality, past studies have identified links between the ADI and Alzheimer's disease risk factors and rates at the individual-level (Powell et al., 2020; Hunt et al., 2020; Dalton et al., 2021); it is possible that the county-level analysis may not have had enough granularity to detect the relationship suggested by prior literature. Indices were moderately related to mental health and well-being; initial U.S. studies have examined the ADI and well-being among cancer patients (Offodile et al., 2022; Rosenzweig et al., 2021); non-U.S. studies have tentatively identified connections between neighborhood deprivation and life satisfaction (Oshio et al., 2021), but this study is among the first to analyze and identify relationships between disadvantage indices and well-being in the U.S. Indices were very related to economic connectedness but moderate for other types of social capital; this is consistent with Chetty et al.'s (2022) finding of strong correlations between intergenerational mobility and connectedness but not other types of social capital. Additionally, positive relationships of cohesiveness with disadvantage index scores may be due to highly cohesive but low-income counties having lower economic connectedness, opportunities, and resources (Chetty et al., 2022).

Variables from the domains of education, including high school and college education, and employment, including employment type and status, were generally most related to life outcomes. This is expected from well-established literature on the links between education and employment with health (Ross and Mirowsky, 1995; Ross and Wu, 1995), which is why these variables are theoretically-relevant building blocks of and are included in all indices. Also, educational attainment is associated with likelihood of unemployment, working full-time, and fulfilling jobs (Ross and Wu, 1995); education and employment are interrelated and may influence life outcomes in tandem. College education and employment type were related to average subjective well-being, which has been seen in previous research on U.S. state-level well-being (Rentfrow et al., 2009). The domain of environment may have been underrepresented since the ADI did not contain variables in this domain; however, toxic exposures and access to healthy food were important for the COI's relationships with outcomes, so including variables that measure the environment should be explored in future research on disadvantage index construction. Sometimes indices are created for specific use cases, such as for COVID-19 (Srivastava et al., 2022) or individual diseases. While certain variables may be more related to certain outcomes, creating new indices for specific outcomes of interest may not be essential; the COI and ADI performed consistently overall and could be useful tools for many applications.

We are not aware of other studies examining relationships of indices across contexts, but studies have investigated indices for specific health outcomes. For example, one study validated its own newly constructed index by comparing it to four alternative measures on predicting chronic disease; however, this study was specific to Medicaid recipients in one state, and not all measures compared are publicly available (Lopez-De Fede et al., 2016). There are concerns within the literature that indices may not be applicable to specific populations or geographic areas (Lopez-De Fede et al., 2016). Thus, further research is needed to validate the consistency of index performance across contexts, populations, and areas within the U.S.

The current analysis is at the county-level since most of the life outcome data are not available at more granular spatial levels, despite the fact that many disadvantage indices are constructed at the sub-county level, e.g., the ADI and COI. This study highlights the need for outcome data to be collected and made available at sub-county levels in order to better measure relationships between disadvantage and life outcomes. Relationships between indices and outcomes may exist at smaller geographic levels, which can be less heterogeneous, that were not apparent at the county-level. We also note that both the ADI and the COI county-level scores are aggregates of smaller spatial levels (the census block group and census tract, respectively). Thus, the results here may be dependent on the aggregation, also known as the modifiable area unit problem (MAUP; (Wong, 2004)).

The strengths and challenges faced by U.S. disadvantage indices are not unique; many countries likewise have indices to measure disadvantage that have similar characteristics. The contemporary literature on disadvantage indices originated and has been most prevalent in the United Kingdom (Phillips et al., 2016), and other countries such as New Zealand (Salmond and Crampton, 2012), Canada (Pampalon et al., 2009), and Switzerland (Panczak et al., 2012) have developed and use national disadvantage indices as well. Disadvantage indices are widely used internationally due to being easily useable at the population-level and reliably associated with health outcomes. However, in other countries there is also a wide range of disadvantage indices, with variation in how many and which variables are included, which also results in differences in how the relationship between disadvantage on health is captured. For example, three disadvantage measures in Scotland resulted in different assessments of health inequalities for certain age groups due to variables such as car ownership and overcrowding (Allik et al., 2016). Disadvantage indices in other countries are also susceptible to being infrequently updated, being dependent on the way national census data is collected, and being produced at varying levels and definitions of geographic areas. Potential measures developed in international contexts that could be used as alternatives or in addition to traditional indices to address these challenges include subjective neighborhood measures (Godhwani et al., 2019) or groupings derived from big data (Wami et al., 2019).

Strengths and limitations: There are various limitations of the study. First, the COI was weighted with the same physically and mentally unhealthy days measures used as physical and mental health outcomes in our comparison. Therefore, the COI cannot be compared on those outcomes, and overall this may slightly inflate the COI's relationship with health outcomes. Second, the CDC censors mortality rates for counties with less than 20 deaths, which limits our ability to evaluate all U.S. counties; there is potential underrepresentation of rural, less populous counties. Third, the ADI does not specify which Census data tables it uses; while we obtained data that matched the description of the variable as closely as possible, it is not possible to confirm that the exact same variable was used in the analysis.

There are several strengths of the study. One strength is that we know of no other studies comparing a variety of publicly available disadvantage indices across a wide range of application contexts. Another strength is that all of the indices and nearly all of the outcomes used in this analysis are publicly available. While the Gallup measures are not, the use of subjective well-being measures is relatively novel in this field at least for the U.S. and provides greater insight beyond traditional health measures. Additionally, the use of a wide range of outcomes relevant to disadvantage strengthens the generalizability of our findings. Finally, our analysis accounts for spatial autocorrelation, which is standard and expected in the field of place-based disadvantage research. Our findings suggest that publicly available indices such as the ADI and COI are robust tools to use across a range of contexts relevant to disadvantage.

Recommendations: The Area Deprivation Index (ADI) is not weighted according to external outcomes, which could potentially confound relationships studied. Therefore, we recommend for the ADI to be used in research when studying relationships between area-based disadvantage and life outcomes. The Child Opportunity Index 2.0 (COI), which is weighted using relevant external outcomes, generalized across all categories of life outcomes in this comparison, and thus may be best suited to identify areas to prioritize for resource allocation. Therefore, we recommend for the COI to be used in real-world policy and decision making.

5. Conclusion

Our study contributes to growing literature on how U.S. disadvantage indices compare on their relationships with relevant life outcomes. Our findings indicate that the Area Deprivation Index (ADI) and Child Opportunity Index 2.0 (COI) are both strong indices to use to relate to a diverse set of outcomes and are useful national-level tools to understand and compare disadvantage across the United States at small-area levels. Particular variables including those in the domains of education and employment most drove the relationships observed for indices with outcomes overall. Future research should explore these relationships at different geographic levels.

Acknowledgments

This research was supported by the Intramural Research Program of the NIH, NIDA.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2023.102997.

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