Incorporating area-level social drivers of health in predictive algorithms using electronic health record data

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ABSTRACT

Objectives: The inclusion of social drivers of health (SDOH) into predictive algorithms of health outcomes has potential for improving algorithm interpretation, performance, generalizability, and transportability. However, there are limitations in the availability, understanding, and quality of SDOH variables, as well as a lack of guidance on how to incorporate them into algorithms when appropriate to do so. As such, few published algorithms include SDOH, and there is substantial methodological variability among those that do. We argue that practitioners should consider the use of social indices and factors–a class of area-level measurements–given their accessibility, transparency, and quality.

Results: We illustrate the process of using such indices in predictive algorithms, which includes the selection of appropriate indices for the outcome, measurement time, and geographic level, in a demonstrative example with the Kidney Failure Risk Equation.

Discussion: Identifying settings where incorporating SDOH may be beneficial and incorporating them rigorously can help validate algorithms and assess generalizability.

INTRODUCTION

Social drivers of health (SDOH)–previously commonly referred to as social determinants of health–measure social structures and individual social factors that impact health, generate disease, and are among the most important contributors to health inequities.[1,2] SDOH encompass multiple domains, including economic stability, education access and quality, health care access and quality, neighborhood and built environment, and social and community context.[3]

There is potential that accounting for non-clinical factors impacting health can improve interpretation, performance, generalizability and transportability of predictive algorithms of health outcomes. While some clinical algorithms contain SDOH, including cardiovascular risk prediction scores,[4,5] their incorporation in algorithms is not routine. This is due, in part, to a lack of recognition of the underlying processes that lead to observed health inequities. There are also problems in availability and quality of individual-level SDOH data.[6–8] It was only in 2024 that the Centers for Medicare and Medicaid Services started requiring SDOH screening for their hospital inpatient quality reporting program.[9] Published clinical algorithms that do use SDOH rely on heterogeneous data sources to calculate SDOH[10] and do not consistently provide detailed motivation for particular measurements. It is also the case that incorporating SDOH in predictive algorithms can potentially worsen disparities by reinforcing inequitable equilibriums via improved prediction accuracy, thereby directing care and resources away from patients in need.[11,12] Thus, it may not always be clear how to identify social factors relevant for a given health outcome, which SDOH data sources to use, or how to integrate them into algorithm development.

One category of well-studied and accessible SDOH variables is area-based social indices and factors, which describe social conditions in particular geographic areas.[13] By definition, indices are composite measures, although some “social indices” in the literature comprise only one factor. We use social index here to refer to both types. Existing guidelines have considered the use of indices in health care payments.[14] In this article, we propose a broader set of considerations for incorporating social indices in predictive algorithms using electronic health records data, summarized in Table 1. We also present the Kidney Failure Risk Equation (KFRE[15]) as an illustration. The KFRE is a risk stratification tool designed to identify chronic kidney disease (CKD) patients at highest risk of progression to kidney failure based on documented age, sex, estimated glomerular filtration rate (eGFR), and urine albumin creatinine ratio (uACR). It was developed using data from a single geographic region and external validation found a stable relationship between the predictors and outcome, attributing observed calibration differences to differences in baseline risk across study samples.[16] The inclusion of social factors in the predictive algorithm could help account for potential differences in baseline risk.

Identifying an index relevant for the algorithm	● How has past literature related SDOH to the outcome? ● Collaborative creation of a causal graph describing underlying systems that created the data ● Which indices contribute to unmeasured nodes in the causal graph? ● What was the original purpose of the indices and is it aligned with the current algorithm? ● Would including SDOH reinforce an unjust equilibrium?
Selecting an appropriate geographic level	● What levels are indices available for? ● Are concepts of interest more appropriately measured in larger or smaller areas? ● Do areas selected correspond to neighborhoods or other homogeneous environments?
Time of measurement	● How long do factors captured in indices take to impact the outcome? ● Does the index show considerable variability over time?
Examining index distributions	● How is the index distributed in the national population vs in the study sample? ● If multiple indices are used, how correlated are they? ● How to divide distribution into quantiles?

Table 1. Guidance on considerations for inclusion of SDOH in predictive algorithms

MOTIVATION FOR INCLUDING SOCIAL DRIVERS

There is ample empirical evidence for associations between SDOH and health outcomes across disease areas.[17] While many health inequities stem from a common set of structural factors and are associated with mutually correlated SDOH,[17] social drivers may contribute differentially across health outcomes. Specific causal pathways may also vary across geographies and settings within them.[18] Additionally, domains of SDOH can be measured in many ways and at multiple levels–from individual to geographic area.[19,20] Hence, careful identification of SDOH domains and measurements relevant for a specific context before inclusion in a predictive algorithm is crucial. For the KFRE, factors across a range of domains, including those related to social status, stress, neighborhood and the health system, have been shown to play a role in CKD incidence and progression to kidney failure.[21–24] These factors contribute to existing disparities in the risk kidney failure incidence, which is 3.3 and 1.5 times higher for Black and Native Americans, compared to whites.[25,26]

Consideration of SDOH is important from the perspective of providing clear conceptual justification for all variables included in the algorithm. In the absence of such conceptual clarity, imperfect proxies, such as race and ethnicity variables, are often used, reifying the erroneous use of race as a biological construct,[27] masking social processes,[28] and possibly contributing to racial health inequities by guiding care away from Black patients.[29] Additionally, because SDOH are often strongly associated with health outcomes,[30] their inclusion in an algorithm may improve predictive performance. This has the potential to lead to improvements in health equity, if, for example, more effective risk stratification leads to targeted interventions for at-risk populations. Including SDOH in algorithms has relevance for transportability. When the development cohort represents a population with a heterogeneous distribution of SDOH associated with the outcome, including SDOH can improve algorithm generalizability to settings with a different distribution of SDOH.[31] Conversely, when the development cohort is homogenous with respect to SDOH, inclusion in the predictive algorithm may be less helpful. However, in these settings, assessing this SDOH homogeneity can still inform the feasibility of transportability to new populations.

AREA-LEVEL SOCIAL INDICES

Social indices are composite area-level measurements often based on government data, such as the American Community Survey (ACS), that can be calculated at the state, county, census tract, census block group, or zip code tabulation area level.[32] Sources of data for indices are scarce because only large-scale surveys are designed to be representative of small areas. Indices can represent multiple dimensions of social factors with a single measure and have been associated with many health outcomes.[33–36]

Social indices are typically developed for identifying at-risk geographic areas to prioritize resource allocation. Table 2 includes examples of indices, along with the motivation for their development and uses that extend beyond their original design. Notably, most measures (with the exception of ICE) do not consider structural racism, which has a pronounced effect on health disparities.[34,37–39]

Index	Purpose and additional uses	SDOH Domains
Social Vulnerability Index (SVI) [40]	Primary: Natural disaster preparedness Additional: Guide COVID-19 testing and vaccine distribution [41]	Socioeconomic status, household composition and disability, minority status and language, and housing type and transportation
Social Deprivation Index (SDI) [33]	Primary: Measuring health care access Additional: Component of a cardiovascular risk score adapted by the American Heart Association [5]	Poverty, nonemployment, household composition and housing quality, transportation and education

Index of Concentration at the Extremes (ICE) [34]	Primary: Measuring disparity extremes Additional: Measuring racial and economic segregation	Minority status and income
Neighborhood Stress Score (NSS) [42]	Primary: Payment risk adjustment for MassHealth	Education, employment, family composition, income and transportation
French Deprivation Score (FDep) [43]	Primary: Analysis and management of spatial health inequities in France	Education, employment, income and transportation
Area Deprivation Index (ADI) [44,45]	Primary: Area inequality measure to assess gradients in mortality. Additional: Incorporated in CMS insurance models [46]	Age, education, employment, family composition, household amenities, housing quality, income and transportation

Table 2. Selected area-level social indices

INCORPORATING INDICES IN PREDICTIVE ALGORITHMS

Decisions about whether and how to include social indices among predictors will vary depending on the outcome, other selected predictors, and composition of the development cohort. These considerations are also relevant when choosing indices for study sample comparisons and stratified evaluation by index.

Identifying relevant indices with causal graphs

The goal of including indices in a predictive algorithm is to capture relationships between social factors and the outcome, and should be informed by prior literature.[47] In the case of progression to kidney failure, factors strongly associated with CKD outcomes include access to care, economic and racial segregation, neighborhood characteristics, as well as stress, social support and family relationships.[21] There is evidence of faster rates of CKD progression in Black and Native American populations[25,26] as well as delayed and lower-quality CKD care provided to Black patients.[24] Appropriate management of early to moderate CKD consists primarily of lifestyle counseling and pharmacological treatment as well as management of prevalent comorbid conditions.[48] We present a simplified representation of these possible causal processes in Figure 1A, distinguishing between area- and individual-level measures. Area income, segregation and neighborhood resources impact levels of access to healthcare, healthy food and safe physical activity, which in turn impact medical care received, diet, and physical activity.

Expressing these relationships with social indices involves identifying factors that incorporate unmeasured nodes in our causal graph. Two candidate indices fulfill those criteria: SDI and ICE (Figure 1B). SDI incorporates measures of poverty, nonemployment, household composition and housing quality, transportation and education.[33] ICE is a joint measure of racial and economic segregation.[34] Among its variants, we consider one which, for a given area i (with population size T_i) compares the number of affluent white individuals (incomes ≥ 80th percentile nationally) A_i to the number of low-income non-white individuals (≤ 20th percentile) P_i: $ICE_i = (A_i - P_i)/T_i$. While SDI and ICE measure overlapping concepts within SDOH domains (e.g., income percentile and percent living in poverty), they each were created to capture domains the other does not (e.g., racial segregation as a measure for structural racism, housing quality). As such, including both can be advantageous.

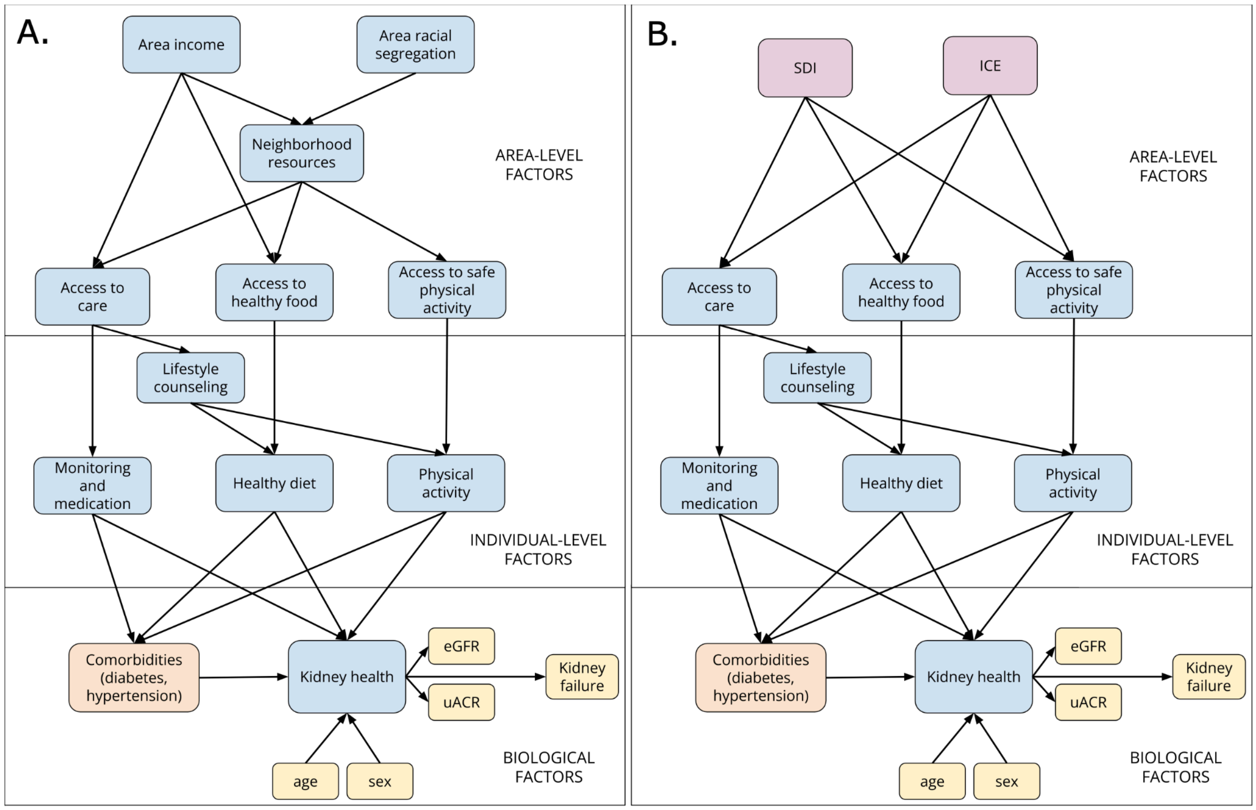

Figure 1. Possible causal graphs representing the relationships between a selected subset of SDOH and variables used in KFRE. Measured variables are shown in yellow (if they are part of KFRE) or orange (if they are not). Unmeasured variables are shown in blue. A. Causal graph with SDOH variables. B. Causal graph with a subset of SDOH variables represented by selected indices (SDI, ICE) in red.

Geography and temporality

Because indices can be calculated at various geographic levels, the same index might have different interpretations and associations with the outcome with consequences for generalizability and transportability.[20] Census tracts, for example, are more consistent in the number of people they capture than counties,[49] and zip codes are designed for delivering mail rather than capturing relatively homogenous geographic areas and population sizes.[20,50] When neighboring geographic areas are heterogeneous with respect to a specific factor used to calculate an index (e.g., poverty), a larger geographic area that applies an average across them may mask those differences.[21] Meanwhile, other factors, such as measures of relative inequality within an area, may not be measurable in small areas. For our KFRE example, we use SDI and ICE indices at the census-tract level to capture heterogeneity across neighborhoods.

The time between measurement of factors used to calculate indices and the outcome may impact the validity of an index for a given predictive task, especially if indices show considerable variation over time, if people move, or if pre-calculated indices are only available for specific years. Prior empirical evidence can help inform how long it takes for factors captured in indices (e.g. income, food access, healthcare access) to affect a given outcome, and how rapidly the factors change over time. Because CKD develops slowly, exposures preceding kidney failure by as much as decades may be relevant for understanding current health. At the same time, current access to healthcare–captured by 2020 ACS-based indices–and effective management of comorbidities may have a larger effect on the speed of decline in later stages, which may be most relevant for the KFRE algorithm.

Distributions

Examining the distributions of indices can help assess collinearity and generalizability. SDI and ICE are 81% correlated at the census-tract level in the general US population. We are interested in studying the KFRE in a primary care setting and introduce a US primary care cohort,[51] examining the SDI and ICE distributions in Figure 2. Figure 2A presents a joint distribution of the indices (correlation -0.83). While lower levels of SDI (lower access) are associated with higher concentrations of wealthy, white individuals in a geographic area (and higher levels of SDI are associated with higher concentrations of poorer, non-white individuals), SDI values for areas with low levels of concentration at the extremes (near ICE=0) are spread across the entire range of the distribution. This provides evidence that it is not redundant to include both in our analysis. Figure 2B depicts the distributions of the two indices in the US population and the primary care cohort. Compared to the US population, the areas where individuals in the cohort reside tend to have higher concentrations of wealthy, white individuals and have higher levels of access to care, however, the populations overlap substantially.

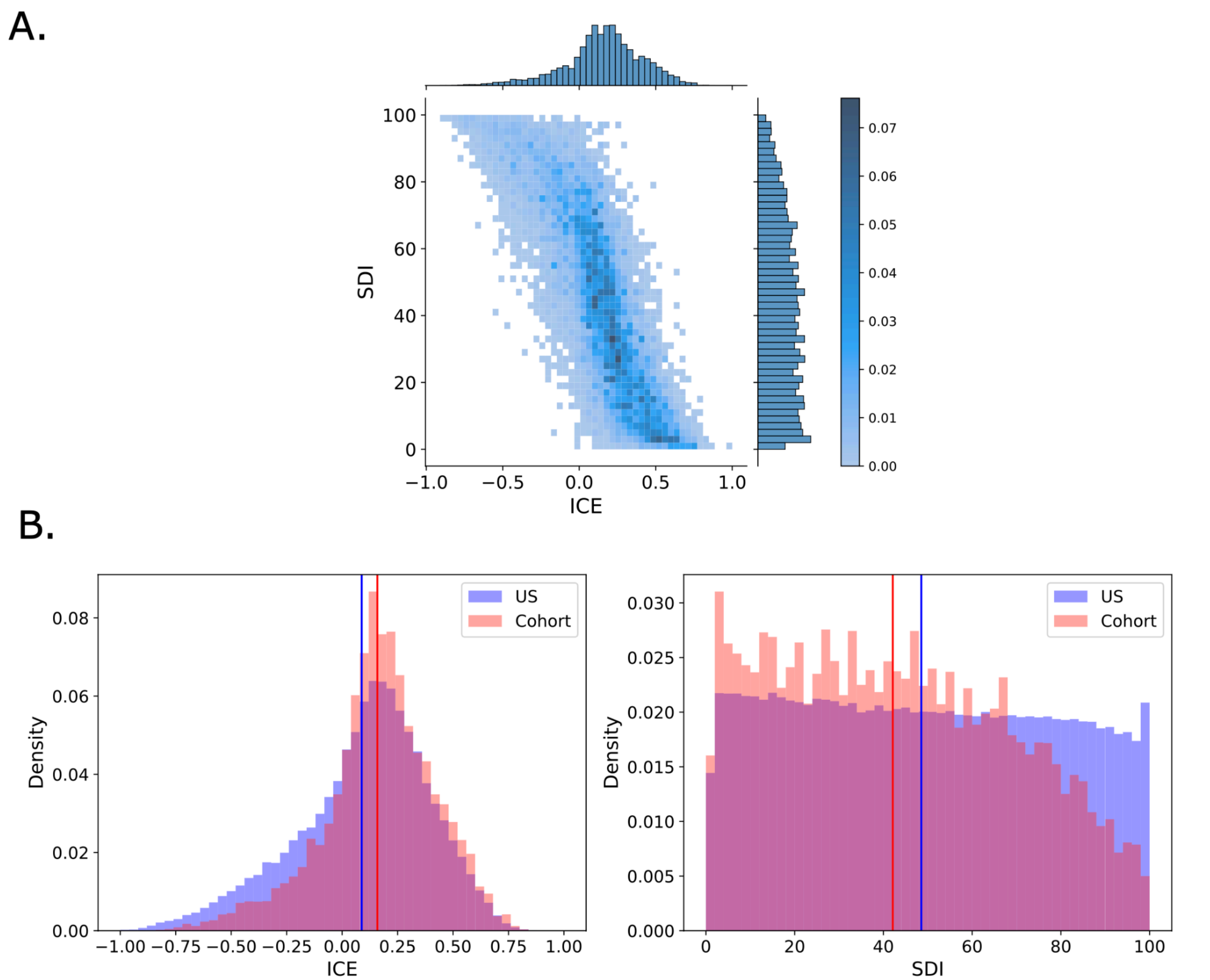

Figure 2. Distributions of 2020 ICE and SDI in a US primary care cohort at the census-tract level. SDI ranges from 0 to 100, with 0 indicating higher levels of access. ICE ranges from -1 to 1, with -1 indicating higher levels of inequality. A. Joint distribution of the two indices. B. Comparisons of the index distributions in the cohort (red) and the general US population (blue) with mean values denoted using vertical lines. The mean values in part B are weighed by the population of each census tract (for US) or number of people in the given census tract (Cohort). In all figures, bars and cells corresponding to fewer than 11 individuals were suppressed for data privacy.

Use of indices for further evaluation of generalizability and transportability

Whether or not indices are included in the predictive algorithm, they can still be useful for reasoning about generalizability and transportability. This may be through stratified evaluation of algorithm performance across quantiles as well as comparison of the distribution of indices between development cohort and target populations or across different study samples. For example, if a distribution of an index differs noticeably between the development cohort and target population, this may suggest that additional validation is necessary to ensure that the relationship captured in the algorithm transports to the target population.[31]

DISCUSSION

SDOH account for many health inequities and are important for designing appropriate interventions to reduce these inequities.[30,52–55] When clinical predictive algorithms are built with electronic health record data, the usefulness of the algorithm may be limited to individuals exposed to a similar, narrow set of social drivers. Consideration of relevant SDOH during algorithm development and evaluation can help validate algorithms and assess generalizability. Previously, no clear broad guidance has been available for identifying settings where incorporating social factors may be beneficial and how to do this rigorously.

We described a starting place for such guidance for incorporating social indices in predictive algorithms (summarized in Table 1) and the implications for interpretation, performance, generalizability, and transportability. These indices have several advantages, including their availability and validation. Despite this, they may not be the most appropriate SDOH variables to include if they reinforce unjust equilibriums or do not sufficiently capture causal paths. Indices reflect conditions of an individual’s environment, which may differ from individual-level factors, and when individual-level factors are most relevant, indices may not be appropriate proxies.[56–58] Similarly, area-level factors may be preferable over indices.[34,59] Moreover, while they have been used in predicting health outcomes,[4,5] the indices were developed primarily for purposes other than building predictive algorithms. Additional validation is warranted for ascertaining whether they are appropriate to use in specific contexts. Finally, developing a more comprehensive set of guidelines for the use of social indices in health algorithms incorporating varied perspectives is an important area of future work.

FUNDING

AF and SR were supported by NIH grant R01LM013989. NG and DHR were supported by Robert Wood Johnson Foundation Grant #79319.

AUTHOR CONTRIBUTIONS

All authors contributed to project conceptualization and formative discussions. AF analyzed PRIME data, under supervision of SR, and wrote the original draft. NG generated and curated social indices data, in collaboration with DHR. All authors reviewed and edited the manuscript.

ACKNOWLEDGEMENTS

The authors thank Professor Alyce Adams, Dr. Robert Phillips, and Dr. Andrew Bazemore for their insights on this work. The authors also thank Malcolm Barrett for code review.

CONFLICT OF INTEREST STATEMENT

None declared.

DATA AVAILABILITY

The following acknowledgment text is included regarding data availability as described by the Stanford Center for Population Health Sciences Data Core (https://phsdocs.stanford.edu/v1.0/need-help/citing-phs-data-core): “Data for this project were accessed using the Stanford Center for Population Health Sciences Data Core. The PHS Data Core is supported by a National Institutes of Health National Center for Advancing Translational Science Clinical and Translational Science Award (UL1TR003142) and from Internal Stanford funding. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH.”

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