

Development and validation of a community risk score for sexual and reproductive health in the United States

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Abstract

Equitable access to sexual and reproductive health (SRH) care is key to reducing inequities in SRH outcomes. Publicly funded family-planning services are an important source of SRH care for people with social risk factors that impede their access. This study aimed to create a new index (Local Social Inequity in SRH [LSI-SRH]) to measure community-level risk of adverse SRH outcomes based on social determinants of health (SDoH). We evaluated the validity of the LSI-SRH scores in predicting adverse SRH outcomes and the need for publicly funded services. The data were drawn from more than 200 publicly available SDoH and SRH measures, including availability and potential need for publicly supported family planning from the Guttmacher Institute. The sample included 72 999 Census tracts (99.9%) in the 50 states and the District of Columbia. We used random forest regression to predict the LSI-SRH scores; 42 indicators were retained in the final model. The LSI-SRH model explained 81% of variance in the composite SRH outcome, outperforming 3 general SDoH indices. LSI-SRH scores could be a useful for measuring community-level SRH risk and guiding site placement and resource allocation.

Lay summary

This paper introduces the Local Social Inequity in Sexual and Reproductive Health (LSI-SRH) score. It is a multipart measure that explores how social factors—such as wealth inequality, housing, and health care access—affect the health of communities, particularly in sexual and reproductive health outcomes. After analyzing social determinants across US neighborhoods, the researchers report that the LSI-SRH score accounts for a substantial amount of inequitable differences in health outcomes. The new risk score can be used to target interventions, influence resource distribution, and inform policy development. This research provides a tool with the potential to drive real change in terms of reducing health disparities and fostering equity.

Key words: sexual health; reproductive health; family planning; spatial analysis; social determinants of health; machine learning.

Introduction

Numerous studies show that social and behavioral determinants of health (SDoH) have a large influence on our health status, accounting for an estimated 80% of health outcomes,¹ and according to the National Academies of Medicine, access to and quality of health care.² The Centers for Disease Control and Prevention (CDC) defines SDoH as the “conditions in which people are born, grow, work, live, and age, and the wider set of forces and systems shaping the conditions of daily life.”³ These wider forces and systems, according to CDC, include social and economic policies, economic and political systems, social norms, racism, and climate change.³

Social and behavioral determinants of health include both protective and social risk factors. Poverty, racism, and housing insecurity are a few of the nonmedical social risk factors associated with poor health outcomes, whereas wealth, social support, and home ownership are associated with better health outcomes.^{4,5} Differences in SDoH and social risk factors play a large role in shaping health inequities and disparities,^{6,7} including those related to sexual and reproductive health (SRH).

In the United States, people who are marginalized because of their age, race, ethnicity, immigration status, income, insurance status, or other nonmedical risk factors are more likely than those without these risk factors to experience inequitable access to SRH services and worse SRH outcomes (eg, unintended pregnancy, infertility, cervical cancer, and sexually transmitted infections [STIs]).⁸⁻¹⁴ In a recent study, Adler et al¹⁵ found that barriers to SRH services increased between 2017 and 2021, especially for historically marginalized people. The American College of Obstetrics and Gynecology has recommended that obstetricians/gynecologists screen for SDoH, refer to social and community resources for addressing SDoH, and acknowledge the role of structural racism in driving SRH outcomes.⁸ The American College of Physicians and the American Association of Family Physicians have taken similar positions.¹⁶

Numerous studies have shown an association between place, SRH outcomes, and access to SRH care. Systematic reviews^{17,18} have summarized evidence showing the positive association between neighborhood deprivation and adverse adolescent SRH (eg, pregnancy and birth rates, contraception, and sexual debut) and perinatal health outcomes. Among

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people living in disadvantaged neighborhoods, Willis et al¹⁹ found lower fertility (ie, conception probabilities) in neighborhoods with the highest vs lowest deprivation score. Ncube et al²⁰ found additional support for the relationship between neighborhood context and both preterm births and low birth weight. Finally, in 5 states, a Kaiser Family Foundation study²¹ of access to SRH care among low-income women showed how service availability and access can vary widely based on state and within-state factors, including state health policies (eg, Medicaid expansion and eligibility levels) and other local factors (eg, health care infrastructure, SDoH, sexual education policies, abortion environment).

SDoH composite indices

Numerous general SDoH indices have been used in the literature to account for neighborhood context.²² Three of the most widely used indices available across the United States—the Area Deprivation Index (ADI), Social Deprivation Index (SDI), and Social Vulnerability Index (SVI)—were developed using factor analysis.²² Willis et al¹⁹ used the ADI to compare differences in conception probabilities between the highest and lowest deciles of disadvantaged neighborhoods, finding that people had reduced fertility in higher-deprivation deciles of the ADI. It should be noted that, while the ADI is one of the most widely used general indices in the literature, it also has known statistical flaws.^{23,24}

Others have worked to develop composite indices specific to SRH. The SRH Burden Index, developed by Rosentel and colleagues²⁵ for Chicago, is a composite of 8 measures: teen births, low birth weight, infant mortality, new HIV diagnoses, people living with HIV, and incidences of gonorrhea, chlamydia, and syphilis. The California Adolescent Sexual Needs Health Index, developed by the California Department of Public Health, is also a composite of 8 measures: number of annual live births to females 19 years old and younger, adolescent birth rate, percentage of live births to adolescents that are repeat births, gonorrhea incidence rate, percentage of youth living in areas of concentrated poverty, percentage of youth living in racially isolated areas, the percentage of 18–24-year-olds without a high school diploma or equivalent, and rural/urban status.²⁶

Study purpose and research questions

Equitable access to SRH health care is key to reducing inequities in SRH outcomes. Publicly funded family-planning services, like those supported by Medicaid, the Title X Family Planning Program, or Section 330 grants (Federally Qualified Health Centers), are an important source of SRH care for people with social risk factors that impede access to SRH care and increase the likelihood of poor SRH outcomes. Improving ways to measure community-level SRH risk that account for SDoH can inform decisions about program placement, resource allocation, and payment.

The 2 goals of this study were to (1) adapt an existing approach to local social inequity measurement²⁷ to create a new, community-level (ie, Census tract) index of Local Social Inequity in SRH (LSI-SRH) based on SDoH and (2) evaluate whether the new LSI-SRH scores are a valid composite measure of community-level risk of adverse SRH outcomes and of the need for publicly funded SRH services. We addressed 3 research questions, as follows:

1. To what extent are key adverse SRH outcomes, such as rates of teen births or STIs, associated with the level of social inequity in communities across the United States?
2. Across US communities, how much of the variation in SRH outcomes is explained by the tailored LSI-SRH scores?
3. How do LSI-SRH scores compare against 3 commonly used, national, area-based composite measures of SDoH and deprivation (ADI, SDI, and SVI) in terms of explaining variation in key adverse SRH outcomes?

Data and methods

Data

The data used for this study were obtained from a large, internally curated SDoH data library (RTIRarity.io) consisting of publicly available data from more than 40 different federal agencies, universities, and nonprofit organizations. The data library includes more than 200 measures of SDoH, as well as health-related measures and information about health resources, such as clinics. In addition, the database includes relevant SRH outcome variables along with ADI, SDI, and SVI values and Guttmacher Institute data on the availability of publicly supported family-planning clinics and potential need for publicly supported contraceptive care.²⁸

The SDoH domains in the database include such measures as the following:

- Community health, well-being, and healthy behaviors: smoking, social support, voter turnout
- Criminal and legal systems: violent crime rates, incarceration
- Demographics: age, sex, race/ethnicity, veteran status
- Health care: insurance coverage, costs, provider supply
- Education: attainment, school quality
- Environment: air quality, drought
- Food: food-assistance rates, access to supermarkets
- Housing: costs, crowding, structural health
- Poverty: income, inequality, unemployment
- Stress, bias, and trauma: racial residential segregation, children in foster care
- Transportation: commuting patterns, infrastructure

Sample

The Census tract, which represents the community or setting in which Title X-funded sites operate, was the unit of analysis for this study. Tracts contain, on average, around 4000 residents. We used data for 72 999 (99.9%) of 73 057 Census tracts (using 2010 boundaries) in the 50 states and the District of Columbia to generate the LSI-SRH scores. We excluded all Census tracts in the US territories and freely associated states and 58 other Census tracts for which we were unable to produce an LSI-SRH score because of missing outcome and predictor data.

Variables

Dependent variable/composite SRH outcome variable

We combined these 5 SRH outcome measures into a composite outcome for the LSI-SRH scores, as follows:

1. Chlamydia incidence per 100 000 (2015–2019 average), county level

2. Gonorrhea incidence per 100 000 (2015–2019 average), county level
3. Low birth weight, percentage of live singleton births less than 2500 g (2014–2018 average), county level
4. Teen birth rate, number of births per 1000 female population aged 15–19 years (2015–2019 average), county level
5. Teen motherhood percentage, historical (among cohort born 1978–1985, percentage of female residents who had a child when aged 13–19 [in 1991–2002]), tract level

For each of the 4 county-level SRH measures, we assigned the county-level value to all the Census tracts within the county. We combined the 5 SRH outcome measures into a single composite outcome by standardizing the outcome measures as z-scores (which have values with a mean of 0 and a standard deviation of 1), summing them, and dividing by the number (5) of SRH outcome measures. All of the variables are from publicly available sources: CDC (measures 1–4) and the Opportunity Atlas (measure 5).

These SRH outcomes were selected because they are publicly available and updated periodically, and because they provide a balanced set of adverse SRH outcomes that would be pertinent to most family-planning clinic visitors. Historical data on teen motherhood (measure 5) were included because these trends often persist from generation to generation,²⁹⁻³¹ and including historical data improves predictions of present-day outcomes.

We considered other SRH outcomes (eg, infant mortality, HIV prevalence) to include in the composite measure but ultimately excluded them because of high rates of missing or suppressed values. It should be noted that, in prior unpublished work by members of the research team, low birth weight, HIV prevalence, and teen birth rates were among the top predictors of infant mortality rates at the tract level. In addition, chlamydia and gonorrhea are highly correlated with HIV prevalence. The strong correlations among these SRH outcomes (Table 1) make them well suited for inclusion in a composite SRH outcome and support the decision to use nonparametric approaches to prediction. Nonparametric approaches do not make any assumptions about the underlying distributions of the data.

Predictor variables

The candidate predictor measures for the composite SRH outcome included validated SDoH measures from an internal database, described earlier. Various measures of need for, or met by, publicly funded family-planning clinics and availability of publicly funded family-planning clinics were sourced from the Guttmacher Institute. We normalized all of the potential predictors to put them on the same scale as the composite SRH outcome. Appendix Table A1 presents a list of the predictors in the initial and final models, as well as the 10 most important predictors.

The predictors in the initial and final models encompassed multiple SDoH domains (see Appendix Table A2): community health, well-being, and healthy behaviors (10 variables); poverty, inequality, and employment (8 variables); demographics (5 variables); environment (4 variables); stress, bias, and trauma (3 variables); food (3 variables); education (2 variables); transportation (2 variables); criminal and legal systems (1 variable); and housing (1 variable). The demographics domain

included race/ethnicity of women potentially in need of publicly funded family planning (3 variables). The health care domain included the percentage of need for publicly funded family planning met by publicly funded family-planning clinics (2 variables).

Analysis

Correlational analyses

We calculated Spearman correlation coefficients for the individual SRH outcome measures, the composite SRH outcome, and the LSI-SRH score (Table 1).

Random forest regression

We used the random forest (RF) algorithm to predict our composite SRH outcome. From the predicted composite SRH outcome, we generated ranked percentile scores for each Census tract, relative to all other tracts. The ranked percentile LSI-SRH scores can be interpreted as risk scores, on a 0–1 scale, with higher values indicating higher risk of adverse SRH outcomes. We present the RF model specifications in Appendix Table A3.

Random forest, an extension of decision trees, is a type of nonparametric model that can be used for both regression and classification problems. The RF approach works by recursively splitting the data into smaller subsets based on the predictors that provide the largest information gain. Each decision tree in an RF is trained on a different, randomly selected subset of the data and is grown to a limited depth, which reduces its complexity and also helps to prevent overfitting. Overfitting occurs when a model is trained too well on the training data and does not generalize well to new, unseen data.

In addition, at each split in the tree, a random subset of the predictors is selected, so that each tree is trained on a different set of predictors. This also makes it more difficult for any single predictor to dominate the tree and cause overfitting. Finally, RF reduces overfitting by combining the predictions of many decision trees, rather than relying on a single tree. This reduces the variance of the model and makes it more robust. When making predictions using the regression approach, the RF takes the average of the predictions from each individual decision tree, and this combination of predictions helps increase the accuracy of the model.

The RF model produces variable importance (VI) metrics that can be interpreted as the amount of error that would be introduced if a particular predictor were removed from the model. We used the normalized VI (VI divided by maximum score) to aid in interpretation and variable selection.

We initially predicted the composite SRH outcome based on 127 SDoH and other measures curated from our internal database. From the initial RF model, we retained 42 predictor variables with a normalized VI >0.2 for the final run of 100 RFs. (See Appendix Table A1 for a list of variables in the initial and final models.)

Imputed scores

Random forest algorithms may include built-in procedures for handling missing data using multiple imputation, depending on the software package. We did not impute missing data for any of the individual SRH outcomes in our composite outcome. Instead, when data were missing for 1 or more of the SRH outcomes, we used linear regression to impute an LSI-SRH score using 56 predictors, including the 42 most

important predictors, where Census tracts had sufficient data. Using this approach, we imputed LSI-SRH scores for 1397 Census tracts, or 1.9% of the total number (73 057) of 2010 US Census tracts (50 states and District of Columbia). After imputation, there were 58 Census tracts without an LSI-SRH score due to lack of available data using this imputation approach.

Validation

Variance explained

We validated the LSI-SRH scores by estimating 6 linear regression models (see [Appendix Table A4](#)) to assess the variance explained by the LSI-SRH score for each of the 5 SRH outcomes and the composite SRH outcome. In all regressions to validate the LSI-SRH score, the LSI-SRH score was the independent variable and the 5 SRH outcomes and the composite SRH outcome were each the dependent variable in separate regressions. The adjusted R^2 from these regressions is interpreted as the percentage of variance in the individual and composite SRH outcomes that is explained by the LSI-SRH scores.

Comparison to other SDoH composite indices

To assess validity relative to “gold standard” SDoH indices, we compared the LSI-SRH score with 3 of the most widely used general indices available across the United States: the 2019 ADI, the 2015 SDI, and the 2018 SVI.²² The 2019 ADI drew on 18 measures in 6 domains, such as education, housing, and transportation, using 2014–2019 data from the American Community Survey (ACS). The 2015 SDI was based on data from 2011–2015 and incorporates 7 measures in 5 domains using Census data. The 2018 SVI was based on 11 measures in 5 domains, using 2014–2018 ACS data.²² We estimated a basic regression for each of the comparison SDoH indices (2019 ADI, 2015 SDI, and 2018 SVI), whereby the SDoH index was the independent variable in separate regressions and the composite SRH outcome was the dependent variable. [Appendix Table A4](#) presents the regression model specifications.

Split-sample validation

In the RF software package we used, approximately one-third of the observations (ie, Census tracts) were kept “out of bag,” meaning that the algorithm was trained on the “in-bag” data, and then the error rates and VI were estimated based on how well the algorithm performed on the “out-of-bag” or held-out data. As an additional check, we randomly split the sample

into 2 equal sizes, ran the same model on both halves, then compared the stability of the VI rankings to assess the possibility of overfitting. All analyses were conducted in StataMP version 17 (StataCorp, College Station, TX) and R version 4.3.2 (R Foundation for Statistical Computing, Vienna, Austria).

Results

As designed, the percentile ranked LSI-SRH scores ranged from 0% to 100%, with a mean of approximately 50%. At the state level, the mean LSI-SRH scores ranged from 3% in New Hampshire and Vermont (lowest risk) to 93% in Mississippi (highest risk) ([Figure 1](#)).

The map ([Figure 1](#)) shows a high concentration of high-risk areas across the southern third of the United States, from Arizona to North Carolina. We also see some higher-risk neighborhoods scattered across the northern states of Montana, North and South Dakota, and rural Minnesota and Michigan, particularly in Native lands. An interactive map of the United States showing the distribution of LSI-SRH scores in 5 risk quintiles and the locations of Title X clinics is publicly available at RTIRarity.io.

With regard to the first research question, [Table 1](#) shows that each of the 5 SRH outcomes was moderately to highly correlated (62%–85%) with the composite SRH outcome, as well as the LSI-SRH scores (58%–86%) based on SDoH. This illustrates the moderate to high degree to which key adverse SRH outcomes are associated with the level of social inequity in communities across the United States. Historical teen motherhood had the highest correlation (85%) with the composite outcome and low birth weight had a moderate association (62%).

With regard to the second research question, [Table 2](#) shows that, overall, the LSI-SRH score explained between 35% and 71% of the variance in the individual SRH outcomes. For example, for every 1-point increase in the LSI-SRH score, one would expect to see a 1.19-point increase in chlamydia incidence, and the LSI-SRH score explains 55% of the variance in chlamydia rates. The LSI-SRH score explains 81% of the variance in the composite SRH outcome across communities.

Finally, when compared with 3 widely used SDoH indices (ADI, SDI, and SVI), we found that the LSI-SRH scores performed substantially better in explaining the variance in the composite SRH outcome measure ([Figure 2](#)). The LSI-SRH scores explained 81% of the variance in the composite SRH outcome measure compared with 19% (SVI), 21% (ADI), and 23% (SDI). To be fair, the other indices

Table 1. Pairwise Spearman rank correlation (rho) coefficients: 5 SRH outcomes, the composite SRH outcome, and the LSI-SRH score ($n = 72\,999$ Census tracts).

SRH outcomes	Chlamydia	Gonorrhea	Low birth weight	Teen motherhood	Teen birth rate
Chlamydia incidence per 100 000, 2015–2019	—	—	—	—	—
Gonorrhea incidence per 100 000, 2015–2019	94%	—	—	—	—
Low birth weight, 2014–2018, %	24%	30%	—	—	—
Historical teen motherhood, %	55%	58%	51%	—	—
Teen births per 1000, 2015–2019	32%	37%	41%	84%	—
Composite SRH outcome	75%	79%	62%	85%	73%
LSI-SRH score	75%	78%	58%	86%	72%

Abbreviations: LSI-SRH, Local Social Inequity in Sexual and Reproductive Health; SRH, sexual and reproductive health.

Source: Authors' analysis of data from the Centers for Disease Control and Prevention (rows 1, 2, 3, 5), the Opportunity Atlas (row 4) (see [OpportunityAtlas.org](#) for details), and an author-developed composite outcome (row 6) and risk score (row 7). Years indicate the years of data averaged to create mean estimates for each tract. Historical: based on data from people born in the United States between 1978 and 1983; teen motherhood in the 1990s was determined using linked tax return data.

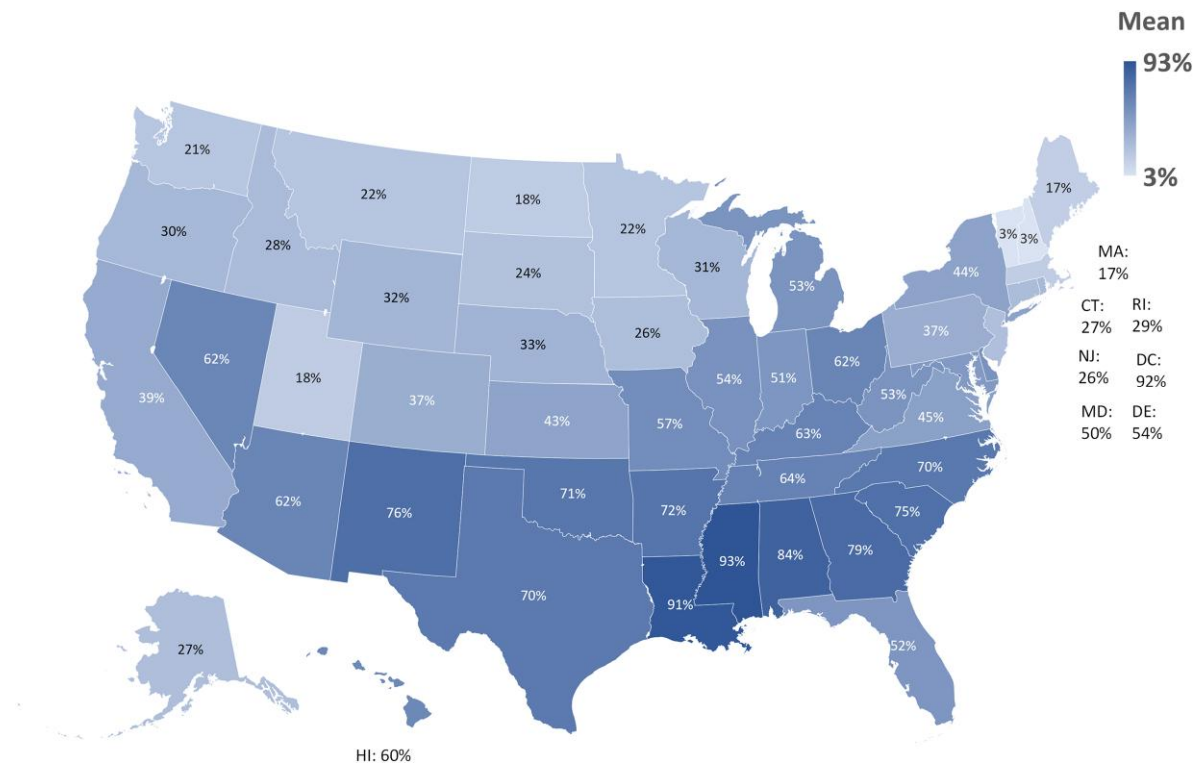


Figure 1. Mean LSI-SRH score by state. Source: Authors’ analysis of an author-developed composite risk score predicting a composite outcome consisting of 5 measures of SRH based on 42 indicators of social determinants of health (see Appendix Table A1). Shown are the mean LSI-SRH scores for each state, indicating relative risk of adverse SRH outcomes based on 42 indicators of social determinants of health. Darker shade indicates higher risk, on average. Abbreviations: LSI-SRH, Local Social Inequity in Sexual and Reproductive Health; SRH, sexual and reproductive health.

Table 2. Variance explained by the LSI-SRH: 5 SRH outcomes and composite outcome ($n = 72\,999$ Census tracts).

Adverse SRH outcome measures	Coefficient for LSI-SRH score	Adjusted R^2
Chlamydia incidence per 100 000, 2015–2019	1.19	0.55
Gonorrhea incidence per 100 000, 2015–2019	2.00	0.58
Low birth weight, 2014–2018, %	0.02	0.35
Historical teen motherhood, %	1.16	0.71
Teen births per 1000, 2015–2019	1.18	0.46
Composite SRH outcome	2.26	0.81

Abbreviations: LSI-SRH, Local Social Inequity in Sexual and Reproductive Health; SRH, sexual and reproductive health. Source: Authors’ analysis of data from the Centers for Disease Control and Prevention (rows 1, 2, 3, 5), the Opportunity Atlas (row 4) (see [OpportunityAtlas.org](https://www.opportunityatlas.org) for details), and an author-developed composite outcome (row 6). Years indicate the years of data averaged to create mean estimates for each tract. Historical: based on data from people born in the United States between 1978 and 1983; teen motherhood in the 1990s was determined using linked tax return data. Pseudo R^2 is a measure of model fit for nonlinear regression analysis. Coefficients and pseudo R^2 statistics indicate the relationship between the LSI-SRH score and the individual measures and composite outcomes being predicted by the LSI-SRH model. For example, for every 1-point increase in the LSI-SRH score, one would expect to see a 1.19-point increase in chlamydia incidence, and the LSI-SRH score explains 55% of the variance in chlamydia alone.

were not designed to predict SRH outcomes, whereas ours was. However, 1 key takeaway from our analyses is that these “gold standard” SDoH indices are not especially good at explaining variance in these SRH outcomes, so a tailored SDoH index is preferred.

Discussion

This paper presents the development, evaluation, and validation of the LSI-SRH score, a measure of the community-level risk of adverse SRH outcomes based on SDoH. The LSI-SRH score outperformed 3 widely used general SDoH indices in explaining variance in our composite SRH outcome measure, explaining 81% of variance compared with 19%–23% for the general indices. This highlights the importance of using an index tailored to SRH outcomes, rather than a general SDoH index, to identify areas with high SRH risk and needs. Importantly, the LSI-SRH score is currently the only measure of community-level SRH risk available for nearly all Census tracts in the United States, covering all 50 states and the District of Columbia.

Rigorous methods were used to estimate the LSI-SRH scores to ensure validity and accuracy. We followed best practices for data science and machine-learning analyses throughout the development, estimation, and validation of the score. For example, we normalized all the variables included in the index, unlike the developers of the ADI.²³ We began with a sound, multidimensional conceptual model informed by social theory and public health principles. We used validated data and applied split-sample validation in addition to the built-in cross-validation. The final result is a score that meets important validity tests for a neighborhood/community index, including conceptual, construct, and predictive validity.³²

The use of RF allowed for robust prediction of SRH outcomes based on the selected SDoH measures. By downscaling county-level outcomes to the tract level, the LSI-SRH scores provide small-area estimates of the overall risk of adverse SRH outcomes within each tract. The tract-level ranked

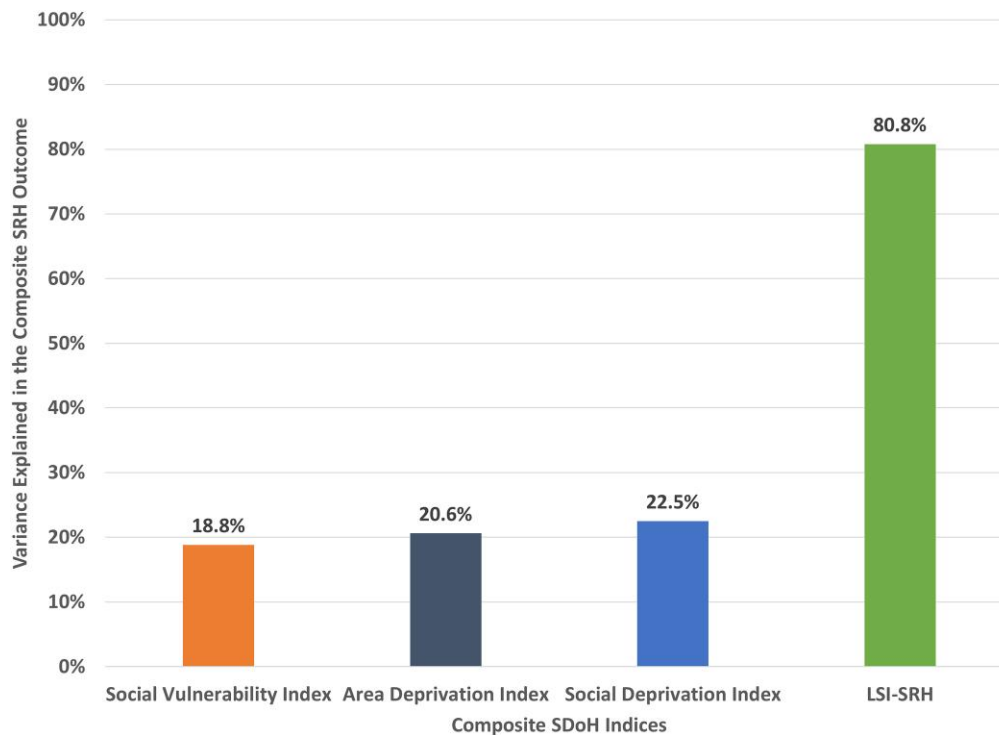


Figure 2. Variance in composite SRH outcome explained by the LSI-SRH score vs other SDoH indices ($n = 72\,999$ Census tracts). Source: Authors' analysis of 3 general SDoH indices (Social Vulnerability Index, Area Deprivation Index, and Social Deprivation Index) and the LSI-SRH score, an author-developed composite risk score predicting a composite outcome consisting of 5 measures of SRH based on 42 drivers of health (see [Appendix Table A1](#)). Variance explained is a measure of model fit based on R^2 statistics. A higher variance explained is better. Abbreviations: LSI-SRH, Local Social Inequity in Sexual and Reproductive Health; SDoH, social determinants of health; SRH, sexual and reproductive health.

percentile risk scores provide a comprehensive, equity-focused measure of SDoH-related risk at the community level.

Policy implications

The versatility of the LSI-SRH scores allows for their application at both individual and community levels to study equitable access. With more than 80% of the area-level risk for adverse SRH outcomes accounted for by the LSI-SRH scores, analyses focusing on individual-level SRH outcomes can thus concentrate on explaining the remaining individual-level variance. Additionally, planners and policymakers can effectively use the LSI-SRH scores to understand current outcomes in relation to past circumstances by stratifying based on community-level risk.

In comparison with existing SRH-focused indices,^{25,26,33} the LSI-SRH score offers several advantages. It is available for nearly all Census tracts in the United States (all 50 states and District of Columbia). It was constructed using a comprehensive set of publicly available county- and tract-level SDoH measures that cover multiple domains of an expanded CDC SDoH framework. It is not limited to adolescents, but instead is relevant to sexually active individuals in general. We explicitly designed it to be useful to the Title X National Family Planning Program to measure and monitor equitable access. Future research is needed to further refine the validity and usefulness of these scores in the real world.

Limitations

There are several limitations of this analysis and the resulting LSI-SRH scores. First, the scores are based on 2010 Census

tract boundaries and data through 2019. When more recent metrics are available, the scores will need to be recalculated using the 2020 tract definitions. Second, given that community factors and SDoH can change over time, regular updates to the LSI-SRH scores will be necessary to ensure their usefulness for future research. Third, the number and types of adverse SRH outcomes that we considered for the composite SRH outcome were limited to those with data that were complete, available at the county or tract level, publicly available, and periodically updated. Two of the 5 SRH outcome measures focused on teen outcomes (teen birth rates and historical teen motherhood). We wish to affirm that inclusion of these measures was not meant to perpetuate stigma. As researchers, we believe that people experiencing these outcomes deserve respect, compassion, and support to reduce stress and stigma they may encounter and to provide them with the resources necessary to succeed. Teen birth rates are an important public health metric, yet we would have preferred to include at least 1 reproductive preference measure (eg, mistimed or unwanted pregnancy). Unfortunately, data on these outcomes were unavailable.

The composite nature of the LSI-SRH scores, which represent the risk of multiple adverse SRH outcomes, may pose challenges in interpretation. Also, since our unit of analysis was the Census tract, the relationship to individual-level risks is unknown. Finally, our measure does not include maternal morbidity or mortality, which are important concerns that were out of the scope of this study given the score's intended use in assessing equitable access to Title X services.

Conclusion

General SDoH composite indices are insufficient for accurately measuring the risk of adverse SRH outcomes based on SDoH. The LSI-SRH model offers an alternative by providing a more precise measure of SRH risk at the community level. Its rigorous construction should make it a useful tool in efforts to study and improve equitable access to family-planning services. For continued relevance and utility, regular updates will be necessary to accommodate changes in outcomes, SDoH, and other community factors.

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Supplementary material

Supplementary material is available at *Health Affairs Scholar* online.

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Conflicts of interest

Please see ICMJE form(s) for author conflicts of interest. These have been provided as supplementary materials.

Notes

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