



Measuring Spatial Social Polarization in Public Health Research: A Scoping Review of Methods and Applications

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Abstract Spatial social polarization (SSP) refers to the uneven spatial distribution and subsequent concentration of polarized social and/or economic groups in a specified geographic area. However, there is heterogeneity in how SSP is measured and operationalized in research. To this end, we conducted a scoping review to characterize the use of SSP measures in public health research, providing a foundation for those seeking to navigate this complex literature, select measurement options, and identify opportunities for methodological development. Using a structured search strategy, we searched PubMed for any primary research, published since 2007, that examined the relationship between SSP and health

outcomes. Across 117 included studies, we found a body of evidence that was primarily set in the United States ($n=104$), published between 2020 and 2022 ($n=52$), and focused on non-communicable diseases ($n=40$). We found that defining SSP in the context of privilege, deprivation, and segregation returns a variety of measures. Among measures, we categorized 18 of them as SSP measures, with the Index of Concentration at the Extremes ($n=43$) being the most common, and 5 of them as composite indices based on numerous underlying variables spanning several domains like education and race/ethnicity. While most employed a single SSP measure ($n=64$), some included up to 5 measures to examine the robustness of findings or to identify how a multidimensional approach to SSP affected associations. Our findings fill a critical literature gap by summarizing options

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for operationalizing SSP measures and documenting their respective methodologies. Future research should consider using multiple SSP measures to capture the multidimensionality of SSP, widen the scope of health outcomes, and clearly explain the choice of measure(s) and methods used to derive them. Our findings can inform future research questions and help guide researchers in the selection and utilization of the various SSP measures.

Keywords Spatial social polarization · Public health · Scoping review · Health equity · Methodology · Social epidemiology · Spatial epidemiology

Introduction

Background

Across the globe, the COVID-19 pandemic catalyzed increased attention to health disparities research [1], this attention added urgency to calls to understand the spatial and social drivers of health disparities for other leading causes of death across populations. Recent research suggests that spatial social inequity, which includes economic and racial/ethnic polarization, operates at multiple levels [2] to affect population health outcomes [3]. Despite such efforts, there remain challenges in how spatial social polarization (SSP) is measured and operationalized in public health research.

Following decades of racial/ethnic and economic segregation in the United States (USA) [4–7], SSP measures have been increasingly used in US public health research to operationalize segregation as an exposure impacting population health [8].

Importantly, while SSP is not a US-only issue [9, 10], the vast majority of research on SSP has been US-based [11], and therefore much of our discussion focuses on US issues. Though it is increasingly common to employ SSP measures in public health research, particularly in the USA, the concept and terminology surrounding SSP, and its measurement have evolved over time. Conceptually, SSP is rooted in theories in the social sciences [12–14], that aim to explain the relational mechanisms by which spatial and social polarization co-occur. While the term SSP may not have a singular universally recognized originator, SSP terminology has been used in the fields of public health [15], geography [16], and sociology [17]. The evolution of the concepts and terminology related to SSP was concurrently marked by advances in SSP measurement.

Defining Spatial Social Polarization

In order to define SSP, we must first define social polarization. Social polarization describes the division of a population into different groups with distinct social and/or economic characteristics which include or can be arrayed as between extremes of privilege and deprivation. Spatial social polarization refers to the uneven spatial distribution and subsequent concentration of polarized social and/or economic groups within a specified geographic area. However, there is little evidence available to guide the selection, utilization, and application of SSP measures.

Development of Measures

The earliest attempt to categorize SSP measures was undertaken by American sociologists, Douglas Massey and Nancy Denton in 1988, with special focus

Table 1 Dimensions of residential segregation for SSP measure classification

Dimension	Definition*
<i>Concentration</i>	The relative physical space occupied by different groups
<i>Evenness</i>	The spatial distribution of different group members within a unit
<i>Exposure</i>	The degree of contact between members of different groups within a unit
<i>Clustering</i>	The degree to which members of different groups cluster in space
<i>Centralization</i>	The location of different groups relative to the center of an urban area or other geographic unit

*Note: As defined by Massey DS and Denton NA. The dimensions of residential segregation. Social forces. 1988;67(2):281–315

on residential segregation [18]. Massey and Denton recognized that residential segregation was not a uni-dimensional construct and aimed to unpack its distinct dimensions (Table 1): concentration, evenness, exposure, clustering, and centralization. Concentration describes the relative physical space that is occupied by different groups [18], and evenness describes the spatial distribution of different group members in a given geography [18]. Exposure describes the degree of contact between members of different groups within a specified geography [18], and clustering describes the degree to which members of different groups cluster in space [18]. Last, centralization describes the location of different groups relative to the center of a geographic unit [18]. While these dimensions were developed in the context of residential segregation, we adapt them here to categorize measures of SSP more broadly.

Implications for Public Health Research

While Massey and Denton provided a foundation for SSP measurement [18], their investigation is limited to residential segregation [19], which may not capture the interrelated dynamics of SSP. In order to examine how different social groups are spatially polarized, we must also consider relevant social systems and resources such as income, education, employment, and housing which are all spatially distributed [20]. This highlights a distinction between measures of residential segregation (which could refer to spatial separation of groups that are equivalent in access to social systems and resources) and measures of SSP. Moving beyond segregation measures, Feldman et al. [8] and Krieger et al. [3] were among the first to employ SSP measures in public health research and extended the measurement of SSP to several domains, including income and a combination of race/ethnicity and income.

This scoping review aims to characterize the use of SSP measures in recent public health literature, according to the dimensions described by Massey and Denton [18], providing a foundation for those seeking to navigate this complex literature, to select among measurement options, or to identify opportunities for further methodological development.

Methods

Information Sources and Eligibility Criteria

We conducted a scoping review of existing evidence to classify and characterize the measurement of SSP in public health research. We searched the National Center for Biotechnology Information database, PubMed, for primary research that employed any measure of SSP as an independent variable in a study of health outcomes among individuals or small area populations. Studies were eligible for inclusion if they met the following criteria: (1) written in English, (2) published between 2007 and 2022, (3) original research that included adjustments for individual-level characteristics, (4) characterized geographic areas smaller than cities or counties (e.g., areal units: neighborhoods, postal codes, and census tracts) with respect to polarization (e.g., to measure effects along a relative scale from deprivation to privilege) or segregation, (5) outcome was related to individual-level health and wellbeing, and (6) outcome was assessed concurrently with the characterization of the geographic area(s).

Search Strategy

To identify relevant studies, we developed a structured search strategy based on search terms from the content of research articles by Feldman et al. 2015 [8], and Krieger et al. 2018 [3]. The structured search strategy was executed on January 2023, as follows: (“state” OR “county” OR “census tract” OR “geographic level”) AND (“spatial social polarization” OR “index of concentration at the extremes” OR “privilege” OR “deprivation” OR “dissimilarity” OR “segregation”). The search terms employed in this scoping review aimed to capture any measure of SSP among geographies smaller than cities or counties, regardless of the health outcome under study.

Study Selection

After executing the search, references were compiled in EndNote, automatically screened for duplicates, and imported into Covidence, a web-based collaboration platform [21], for evidence screening and synthesis. References were subjected to independent

abstract screening by two members of the research team (i.e., EMM and DM) based on the eligibility criteria, with disputes resolved via consensus by a third member (i.e., HSAM) of the research team. Following the abstract screening, we accessed the full-text versions of eligible references and proceeded with the data abstraction process.

Data Abstraction Process and Data Items

Eligible references were abstracted to assemble information on publication year, study design, study setting, study population, sample size, health outcome(s), and characteristics of SSP measures including SSP measure name, SSP measure formula (if available), and related domain(s). Information collected during the data abstraction process was independently documented and verified by another member of the research team.

Methods of Analysis and Synthesis of Results

Following screening, selection, and data abstraction, results were synthesized based on relevant study attributes and SSP measure characteristics. First, studies were grouped according to the data items described above. Health outcomes were classified, using the methods described by Henson et al. 2020 [22], as either: non-communicable diseases, communicable diseases, mortality, general physical health, maternal and perinatal health, injuries, general mental health, or quality of life. Then, we systematically characterized each SSP measure according to the dimensions described by Massey and Denton [18] (Table 1), and compiled a list of unique SSP measures employed across the body of literature. A summarized description of each measure included the following: the measure formula, applicable domains (e.g., race/ethnicity, income, education), and accompanying references. Finally, we tabulated results for presentation as guided by the Preferred Reporting Items for Systematic Review and Meta-Analysis Extension for Scoping Reviews (PRISMA ScR) [23, 24] and provided a narrative synthesis. In this scoping review, we adopted a flexible approach to synthesis using scoping review methodology [25] rather than adhering to a predefined study protocol.

Results

Search and Study Selection

Our primary search initially identified 465 articles (Fig. 1). We excluded 310 articles based on title/abstract review. We retrieved 155 full-text articles for eligibility assessment, leading to the exclusion

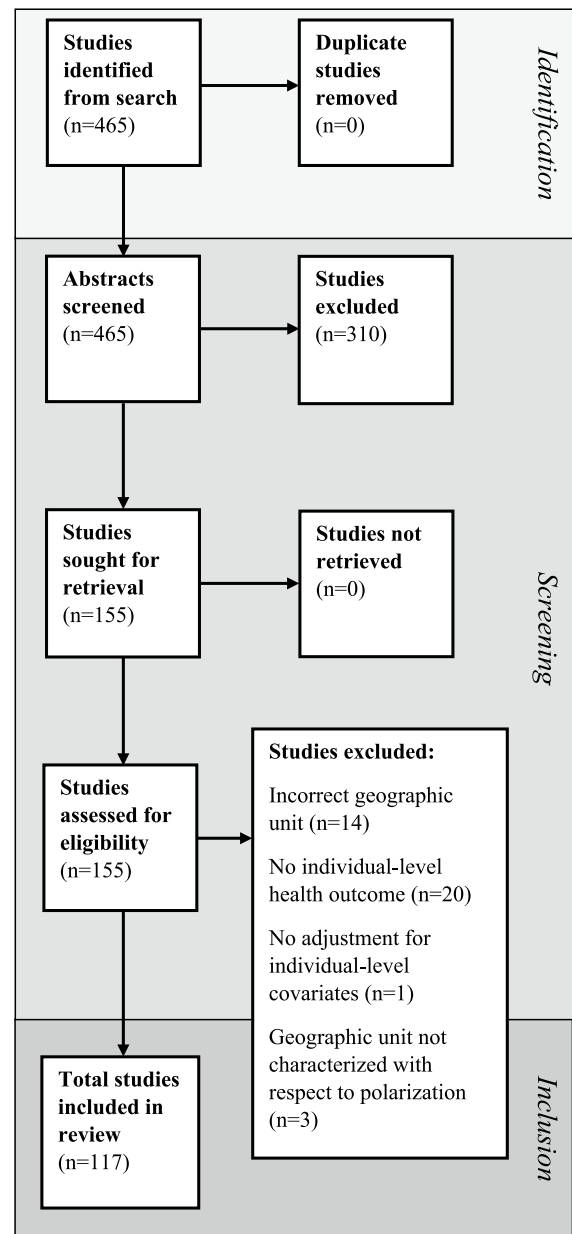


Fig. 1 PRISMA flowchart

of 38 articles. Reasons for exclusion included geographic measurement scale (i.e., no geographic units considered smaller than cities or counties), no individual-level health outcome, no measurement of polarization or segregation, and not original research. Post-eligibility assessment, we included 117 articles in the review.

Overview of Studies

The characteristics of included articles ($n=117$) are presented in Table 2. We identified a wide body of literature published between 2007 and 2022 that indicates a clear trend by publication year; 34.2% ($n=40$) was published between 2015 and 2019, and nearly 45% was published ($n=52$) from 2020 to 2022. A majority of the studies were set in the USA ($n=104$), followed by Canada ($n=10$). Among included articles, the median sample size was 21,403 with an interquartile range of 144,673 (Q1: 2678, Q3: 147,351). Across included articles, nearly 46% of the evidence employed a cohort design ($n=54$), and 42% employed a cross-sectional design ($n=49$). The number of SSP measures used in each study varied, 54.7% ($n=64$) utilized 1 SSP measure, 36.8% ($n=43$) utilized between 2 and 3 different SSP measures, and 8.5% ($n=10$) utilized 4 to 5 different SSP measures. As for health outcomes, most studies focused on non-communicable diseases ($n=40$) followed by mortality ($n=27$), general physical health ($n=16$), maternal/perinatal health ($n=15$), injuries ($n=7$), communicable diseases ($n=6$), general mental health ($n=3$), and quality of life ($n=3$).

Measurement Classification

Of the 23 measures identified by our review, 18 were SSP measures and 5 were composite indices. SSP measures that were clearly defined were classified according to the dimensions of residential segregation described by Massey and Denton [18], and are presented in Table 3; which describes each of the 18 SSP measures, and provides a brief background, the measure formula, formula details, annotated strengths and limitations, plus relevant domains. While some measures are exclusively used for SSP research (e.g., Index of Concentration at the Extremes [ICE]), others are measures that are not specific to SSP research, though

Table 2 Characteristics of included studies

Total (<i>n</i>, <i>n</i>%)	117	100%
Publication year (<i>n</i>, <i>n</i>%)		
2007 to 2009	9	7.7%
2010 to 2014	16	13.7%
2015 to 2019	40	34.2%
2020 to 2022	52	44.4%
Country (<i>n</i>, <i>n</i>%)		
United States	104	88.8%
Canada	10	8.5%
Italy	1	0.9%
France	1	0.9%
India	1	0.9%
Study design (<i>n</i>, <i>n</i>%)		
Cohort	54	46.2%
Cross-sectional	49	41.9%
Other	10	8.5%
Case-control	2	1.7%
RCT	2	1.7%
Health outcomes (<i>n</i>, <i>n</i>%)		
Non-communicable diseases	40	34.2%
Mortality	27	23.1%
General physical health	16	13.6%
Maternal and perinatal health	15	12.8%
Injuries	7	6.0%
Communicable diseases	6	5.1%
General mental health	3	2.6%
Quality of life	3	2.6%
Sample size (mean, SD)		
	3,997,718	30,477,369
Number of SSP measures employed (<i>n</i>, <i>n</i>%)		
1 exposure measure	64	54.7%
2–3 exposure measures	43	36.8%
4–5 exposure measures	10	8.5%

are utilized in this context in the research presented here (e.g., Getis-Ord G^* and relative ratios).

The 5 composite indices identified by our review, cannot be classified according to Massey and Denton's Dimensions of Residential Segregation [18], as they are based on several underlying factors, and encompass subjectively labeled domains, such as socioeconomic status. Moreover, the basis of comparison differs between SSP measures and composite indices; SSP measures compare polarization among privileged and

Table 3 Spatial social polarization (SSP) measure details

Name	Background	Formula	Formula details	Strengths and limitations	Dimension	Domain	References
Index of Concentration at the Extremes (ICE)	ICE was initially developed to measure economic polarization in both privileged and deprived groups simultaneously using 1 measure [19]. It was extended in 2015 to capture both racial and economic disparities [26]. ICE is a continuous measure that ranges from -1 to 1, negative values indicate concentrated deprivation and positive values indicate concentrated privilege	$ICE_i = \frac{(A_i - P_i)}{T_i}$	<p>A_i = Number of privileged persons in areal unit i (e.g., in 80th income percentile)</p> <p>P_i = Number of deprived persons in areal unit i (e.g., in 20th income percentile)</p> <p>T_i = Total population with known income level in areal unit i</p>	<p>STRENGTHS: Single metric avoids issues of multicollinearity that are common when separate measures of privilege and deprivation are used</p> <p>LIMITATIONS: Choice of distribution cutoff points affects classification as either privileged or disadvantaged</p>	Concentration	<p><i>Income</i></p> <p><i>Race</i></p> <p><i>Race/Income</i></p> <p><i>Education</i></p> <p><i>Language</i></p> <p><i>Nativity</i></p> <p><i>Home ownership</i></p>	<p>[3, 8, 15, 26–54]</p> <p>[3, 8, 15, 26, 27, 29–39, 41, 42, 45, 55, 46, 47, 50–54, 135–138]</p> <p>[3, 8, 15, 26, 27, 30–37, 41–43, 45–47, 50–52, 56–60]</p> <p>[8, 26, 53]</p> <p>[53, 61]</p> <p>[53]</p> <p>[36]</p>
Index of Dissimilarity (Dissimilarity Index, Duncan Index of Dissimilarity)	The dissimilarity index (D) was initially developed in 1955 to measure occupational segregation [62], and adapted to measure residential segregation [18]. It represents the proportion of a group that would need to move to achieve a uniform population distribution. The minimum value of 0 corresponds to no dissimilarity, and the maximum of 1 corresponds to complete segregation or separation. This index can be adapted to spatial data using the spatial dissimilarity index [63]	$D = \frac{1}{2} \sum_{i=1}^n \left \frac{w_i}{W_T} - \frac{b_i}{B_T} \right $	<p>n = Total number of areal units in the study area</p> <p>w_i = Number of individuals in group w, in areal unit i</p> <p>W_T = Total number of group w individuals in the study area</p> <p>b_i = Number of individuals in group b, in areal unit i</p> <p>B_T = Total number of group b individuals in the study area</p>	<p>STRENGTHS: Easy to compute, and easy to interpret. Can be used to compare overall segregation levels within a geography over time, or between different geographies</p> <p>LIMITATIONS: Binary measure only captures segregation that exists between two groups at a single point in time. Does not provide a single value for all groups, which may conceal segregation among other (2+ groups). D becomes increasingly unstable as the overall population, or populations of comparison groups decreases. Aspatial index does not consider the proximity of various areal units</p>	Evenness	<p><i>Race</i></p> <p><i>Income</i></p>	<p>[42, 55, 64–73, 89, 139–146]</p> <p>[74]</p>

Table 3 (continued)

Name	Background	Formula	Formula details	Strengths and limitations	Dimension	Domain	References
Isolation Index	The isolation index was initially proposed by Bell [75], refined by Lieberman [76], and formally defined by Massey [18], to measure the extent to which minority group members are exposed to other minority group members, using a weighted average for each unit's minority proportion. Index ranges from 0 to 1 and represents the probability that a minority group member shares a unit with another minority group member [77]	$I = \sum_{i=1}^n \left[\left(\frac{x_i}{X} \right) \left(\frac{x_i}{n} \right) \right]$	<p>n = The number of areal units in the study area, ordered smallest to largest by land area</p> <p>x_i = The minority population of areal unit i</p> <p>X = The sum of all x_i (i.e., the total minority population)</p> <p>t_i = The total population of areal unit i</p>	<p>STRENGTHS: Measures the relative dissimilarity of the distribution, regardless of any difference in group size. Can remove asymmetry by using methods like the "Local Krivo Isolation Index" or "Correlation Index"</p> <p>LIMITATIONS: Asymmetry when 2 groups have the same proportion in the population. Earlier formulations rely on absolute size of groups [75, 76]</p>	Exposure	Race	[32, 45, 65, 69, 71, 73, 78–91]
						Income	[74]
Relative Ratios	Relative ratios are a method to measure relative concentration, which denotes measures of frequency to provide a relative comparison between groups. Values range from $-\infty$ to ∞ , and interpretation varies according to the choice of comparison/referent group	$RR_i = \frac{A_i}{B_i}$	<p>A_i = The measure of frequency in the deprived (i.e., comparison) group, for areal unit i</p> <p>B_i = The measure of frequency in the privileged (i.e., referent) group, for areal unit i</p>	<p>STRENGTHS: Simplistic yet flexible measure of population composition</p> <p>LIMITATIONS: Employing 2 or more comparison groups necessitates multiple comparisons</p>	Concentration	Race	[92–96, 147, 148, 149]
						Income	[44, 92, 96]
Gini Coefficient (Gini Index)	The Gini coefficient (G) was developed by Corrado Gini in 1912, as a relative measure of income inequality [97]. The Gini coefficient is a measure of inequality among particular values of a frequency distribution. A coefficient of 0 indicates perfect equality, and 1 indicates perfect inequality	$G = 1 - \sum_{i=1}^n (p_i)^2$ $Gb = 1 - \sum_{i=0}^{n-1} (Y_{i+1} + Y_i)(X_{i+1} - X_i)$	<p>n = The total number of areal units</p> <p>p_i = The probability of an areal unit being assigned a particular value of a distribution</p> <p>Y_i = The cumulative proportion of the variable in group i</p> <p>X_i = The cumulative proportion of the population in group i</p>	<p>STRENGTHS: Single summary statistic allows for the examination of inequities in 1 variable, or 2 variables using Browns Formula (Gb) [98]</p> <p>LIMITATIONS: G alone cannot differentiate between different types of inequities. The characteristics of Gb are not well documented</p>	Evenness	Race	[45, 99]
						Income	[72, 78]

Table 3 (continued)

Name	Background	Formula	Formula details	Strengths and limitations	Dimension	Domain	References
Krivo Local Isolation Index	The Krivo Local Isolation Index was developed to measure segregation [100]. It measures the areal unit-level probability of interaction between individuals belonging to 2 different groups compared with what would be expected in the entire study area (e.g., city) if residents were not spatially clustered. Positive values indicate a proportionate decrease in the chance of interaction between groups X and Y compared with the probability of random interaction in the study area [101]. Negative values indicate greater exposure among groups	$LS_{Isol_{key}} = 1 - \frac{(\sum_{ij} c_{ij} p_{ij}) / (\sum_{ij} c_{ij} (c_{ij} p_{ij})^h)}{(\sum_{ij} c_{ij}) / (\sum_{ij} (c_{ij} p_{ij}))}$	<p>x = The number of people in group X that live in areal units i and j</p> <p>y = The number of people in group Y that live in areal units i and j</p> <p>c_{ij} = The value of cell ij in a spatial weights' matrix, which equals 1 if areal units i and j share a border or if i = j, and 0 otherwise</p>	<p>STRENGTHS: Provides a localized measure of the probability of interaction between individuals in two groups within specific areal units. By considering a spatial weights matrix that accounts for shared borders, the index incorporates the spatial context of areal units. Accounts for the asymmetry inherent to the "Isolation Index"</p> <p>LIMITATIONS: Limited to the comparison of 2 groups, and results may be sensitive to the chosen spatial scale of analysis</p>	Exposure	Race Income	[101] [101]
Local Getis Ord G* statistic	G* statistics are z-scores that assess how different the racial composition of a particular areal unit and its neighboring units are, compared to the mean racial composition of the larger study area (e.g., city). The z-scores and accompanying p-values tell us where units with high or low values spatially cluster, with larger z-scores indicating greater spatial clustering of high values, and smaller z-scores indicating greater spatial clustering of low values. A p-value will be statistically significant if an areal unit with high values is surrounded by other units with high values [102]	$G_i^* = \frac{\sum_{j=1}^n w_{ij} x_j - \bar{X} \sum_{j=1}^n w_{ij}}{S \sqrt{\frac{1}{n} \sum_{j=1}^n w_{ij}^2 - \frac{(\sum_{j=1}^n w_{ij})^2}{n^2}}}$ <p>where</p> $\bar{X} = \frac{\sum_{j=1}^n x_j}{n}$ $S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - (\bar{X})^2}$	<p>x_i = Attribute value (e.g., % population belonging to a certain social group) for areal unit j</p> <p>w_{ij} = The spatial weight between areal units i and j</p> <p>n = Total number of areal units</p>	<p>STRENGTHS: Useful for hot spot analyses. Can adapt to larger geographies and assess clustering by using the Global Getis Ord G* statistic</p> <p>LIMITATIONS: There exists a trade-off between the accuracy of the G* statistic and the precision of the search radius, reducing the search radius tends to reduce the number of areas with significant p-values</p>	Clustering	Race	[103–108]

Table 3 (continued)

Name	Background	Formula	Formula details	Strengths and limitations	Dimension	Domain	References
Location Quotient	Location quotient measures the relative concentration (i.e., proportion), of minority group members in the study area (e.g., city) compared to the proportion in a particular areal unit (e.g., census tract) [109]. Location quotient ranges from 0 to ∞ ; lesser values indicate that the proportion of minority group members in the smaller areal unit is less than the proportion of the same group in the entire study area. Larger values indicate that the proportion of minority group members in the areal unit is greater than the proportion of the same group in the entire study area	$LQ_{im} = \frac{(\frac{x_{im}}{x_i})}{(\frac{y_m}{y})}$	LQ_{im} = The value of the i^{th} areal unit in a study area for minority group m x_{im} = The number of individuals from minority group m living in the i^{th} areal unit x_i = Total number of residents in the i^{th} areal unit y_m = Total number of individuals from minority group m in the study area y = Total number of residents in the study area	STRENGTHS: Measure compares 2 areal units and allows us to examine relative deprivation LIMITATIONS: LQ_{im} is sensitive to small-area estimation therefore diminished population sizes may bias the magnitude of LQ_{im}	Concentration	Race	[109–111]
Redlining Index	A measure of the relative disparity in mortgage loan denial between 2 groups. The redlining index uses a pooled odds ratio (OR) to place each area along a continuum of disparities in mortgage loan denial. Interpretation follows that of pooled ORs, such as those estimated by the Mantel–Haenszel method. This is not to be confused with “historical redlining scores”, which rely on historical HOLC grades and grade weights	$OR_{loan\ denial} = \frac{\sum_{i=1}^k (\frac{a_i d_i}{n_i})}{\sum_{i=1}^k (\frac{b_i c_i}{n_i})}$	a_i = The number of individuals in group 1 that had approved loans d_i = The number of individuals in group 2 that had denied loans b_i = The number of individuals in group 1 that had denied loans c_i = The number of individuals in group 2 that had approved loans n_i = The total number of individuals in groups 1 and 2	STRENGTHS: Can apply stratified models or random effects models to account for multilevel geographies LIMITATIONS: Offers limited insight on historical redlining, as HOLC grades are not involved in calculating the redlining index. Due to the non-collapsibility of the OR, the estimates of the conditional OR may differ from the marginal OR	Concentration	Race	[64, 112]

Table 3 (continued)

Name	Background	Formula	Formula details	Strengths and limitations	Dimension	Domain	References
Entropy (<i>Information Index</i>)	The entropy index was developed as a measure of segregation by Theil & Finizza [113]. Entropy describes the extent of a study area's racial/ethnic diversity and reaches its maximum when each racial/ethnic group is equally represented in the study area [77]. The entropy index provides a weighted measure of each areal unit's departure from the study area's entropy. The entropy index varies between 0 and 1; a value of 0 corresponds to all areal units having the same composition as the city, and a value of 1 corresponds to all units being composed of only 1 group	$H = \frac{\sum_{i=1}^n t_i(E-E_i)}{ET}$ <p>where</p> $E = P \ln\left(\frac{1}{P}\right) + (1-P) \ln\left(\frac{1}{1-P}\right)$ $E_i = p_i \ln\left(\frac{1}{p_i}\right) + (1-p_i) \ln\left(\frac{1}{1-p_i}\right)$	<p>P = Proportion of minority group members to total population in a study area</p> <p>P_i = Proportion of minority group members to total population in areal unit i</p> <p>T = Total population of majority group members and minority group members in the study area</p> <p>t_i = Total population of majority group members and minority group members in areal unit i</p>	<p>STRENGTHS: Measures the spatial distribution of multiple groups simultaneously, while capturing racial/ethnic diversity</p> <p>LIMITATIONS: Scale dependent and sensitive to outliers, meaning that extreme values may significantly impact the index</p>	Evenness	Race	[65, 79]
Delta (<i>Delta Index</i>)	The Delta index was founded by Hoover [114], and adapted to measure spatial concentration [115]. The Delta index calculates the percentage of minority members living in an areal unit with an above-average concentration of minority residents. The maximum and minimum values of the delta index are 1 and 0, indicating the proportion of a minority group that would have to move in order to achieve a uniform density across units [77]	$Delta = 0.5 \sum_{i=1}^n \left \frac{x_i}{X} - \frac{a_i}{A} \right $	<p>n = The number of areal units in the study area, ordered smallest to largest</p> <p>x_i = The minority population of areal unit i</p> <p>X = The sum of all x_i (i.e., total minority population in the study area)</p> <p>a_i = The land area of areal unit i</p> <p>A = The sum of all a_i (i.e., total land area in the study area)</p>	<p>STRENGTHS: Easy to compute and interpret</p> <p>LIMITATIONS: Requires information on the land area occupied by each unit</p>	Concentration	Race	[78, 79]

Table 3 (continued)

Name	Background	Formula	Formula details	Strengths and limitations	Dimension	Domain	References
Spatial Proximity Index (Index of Spatial Proximity)	The Spatial Proximity index (SP) was first proposed by White [17], as an index to measure the spatial clustering of groups. The index corresponds to the average intra-group proximities, weighted by the proportion of each group in the population [77]. SP = 1 corresponds to no differential clustering between majority (Y) and minority (X) group members, SP > 1 indicates that members of each group live closer to one another than to members of the other group (e.g., more clustering), and SP < 1 indicates that members of both groups live closer to each other than to members of their own group (e.g., less clustering)	$SP = \frac{(XP_{xx} + YP_{yy})}{TP_n}$ <p>where</p> $P_{gg} = \sum_{i=1}^n \sum_{j=1}^n \frac{(g_i g_j d_{ij})}{G^2}$ <p>(g, G) = (x, X), (y, Y), (t, T)</p> $Relative\ Clustering = \frac{P_{xx}}{P_{yy}} - 1$	x_i, x_j = The minority population of areal units i or j X = The total minority population of the study area y_i, y_j = The majority population of areal units i or j Y = The total majority population of the study area t_i, t_j = The total population of areal units i or j T = The total population in the study area P_{xx} = The average proximity between minority group members P_{yy} = The average proximity between majority group members P_u = The average proximity among all members of the population $c_{ij} = \exp(-d_{ij})$, Transformation of the distance between centroids of areal units i and j (d_{ij})	STRENGTHS: Spatial index considers the proximity of various neighborhoods. Can derive a measure of “Relative Clustering” by subtracting one so that index ranges from 0 to 1.0, with higher values reflecting higher segregation [18] LIMITATIONS: Application is limited to situations where the spatial arrangement of population groups is a key concern. Index may be sensitive to the chosen geographic scale of analysis	Clustering	Race	[73, 79]

Table 3 (continued)

Name	Background	Formula	Formula details	Strengths and limitations	Dimension	Domain	References
Exposure Index (<i>Interaction Index</i>)	The Exposure Index, or Interaction Index was defined by Lieberman in 1981 [116], as the probability that a randomly drawn member of the minority group shares an area with a member of the majority group. The exposure index measures the extent to which minority group members are exposed to majority group members. The exposure index ranges from 0 to 1, lower values indicate greater segregation among groups and higher values indicate less segregation among groups [18]. The interaction index can complement the "Isolation Index", in a 2-group comparison the Isolation and Interaction Indices sum to 1; lower values of interaction and higher values of isolation are both indicative of greater segregation	$xI^{*}y = \sum_{i=1}^n [(\frac{x_i}{X})(\frac{y_i}{Y})]$	<p>n = The number of areal units (e.g., census tracts) in the study area, ordered smallest to largest by land area</p> <p>x_i = The minority population of areal unit i</p> <p>X = The sum of all x_i (total minority population in the study area)</p> <p>y_i = The majority population of areal unit i</p> <p>t_i = The total population of areal unit i</p>	<p>STRENGTHS: When employed with the "Isolation Index", it can be used to assess segregation in terms of overall residential exposure. Allows for the comparison of inter- and intra-group probabilities</p> <p>LIMITATIONS: Binary focus may oversimplify the complexity of multi-group interactions such as those found in diverse populations. Scale dependent index does not capture the spatial arrangement of groups within an area and depends on the relative sizes of groups being compared (i.e., asymmetric)</p>	Exposure	Race	[64]

Table 3 (continued)

Name	Background	Formula	Formula details	Strengths and limitations	Dimension	Domain	References
Kernel Density Estimation	Kernel Density Estimation (KDE) is used to summarize the spatial distribution and clustering of a population. KDE methods have been extended to accommodate spatial data, which can be used to measure residential segregation. Relative composition and subsequent clustering are measured by multiplying sample data by a probability density function that is continuously applied across the data, then summing results to yield a single estimate of the underlying probability density function [117]. Resulting KDE estimates can be divided by the total population and multiplied by 100 to provide the percent of group members at each population-weighted centroid	$y(x) = \frac{1}{n} \sum_{i=1}^n K\left(\frac{x-X_i}{h}\right)$ $K(r) = c(h) \left(1 - \left(\frac{r}{h}\right)^2\right)$ <p>where $r < h$, 0 otherwise $c(h) = \frac{3}{\pi h^2}$</p>	<p>y = The estimated probability density function</p> <p>X_i = The minority population of areal unit i</p> <p>x = The sum of all X_i (i.e., total minority population in the study area)</p> <p>K = The kernel function; spatially, it can be expressed as a function of r</p> <p>r = Distance from kernels central point</p> <p>h = Kernel bandwidth</p> <p>c(h) = Scaling factor to ensure function sums to unity</p>	<p>STRENGTHS: Provides better estimation of a population's spatial distribution beyond histograms. Population data for neighboring census tracts are incorporated in measuring an areal unit's racial residential segregation. Provides a smooth and continuous representation of the underlying probability density function</p> <p>LIMITATIONS: Tends to over smooth near the boundaries of the data, leading to underestimation of density near the edges of the observed range; known as the boundary effect. KDE can be computationally intensive. Choice of bandwidth is often subjective, and different bandwidths may lead to different interpretations of the data</p>	Clustering	Race	[118]

Table 3 (continued)

Name	Background	Formula	Formula details	Strengths and limitations	Dimension	Domain	References
Atkinson Index	The Atkinson Index was designed to evaluate segregation and income inequality [119]. The Atkinson Index allows for the differential weighting of units at different points along the distribution; weights are decided by the researcher using the shape parameter and correspond to areas of where minority group members are either over- or under-represented. Larger values of the shape parameter (b: 0.5–1) indicate areas where the proportion of minorities is greater than the study area average (e.g., over-representation); smaller values (b: 0–0.5) indicate units where the proportion of minorities is smaller than the study area average (e.g., under-representation) [77]. A shape parameter of 0.5 indicates that both areas contribute equally. Both b & AI range from 0 to 1; 0 for minimal segregation, 1 for maximum segregation [77]	$AI = 1 - \left(\frac{P}{1-P} \right) \frac{1}{P^T} \sum_{i=1}^n [(1-p_i)^{(1-b)} p_i^b t_i] \left(\frac{1}{T} \right)$	<p>P = The ratio of minority group members (X) to the total population (T)</p> <p>t_i = The total population of areal unit i</p> <p>T = The total population in the study area (i.e., sum of all t_i)</p> <p>p_i = The ratio of minority group members (x_i) to the total population in areal unit i (t_i)</p> <p>b = The shape parameter</p>	<p>STRENGTHS: The Atkinson Index allows for the incorporation of different levels of inequality aversion through the shape parameter. Different values of b lead to different Atkinson Indices, providing a range of inequality measures. It is size invariant; the measure is unchanged when the number of individuals in each group is multiplied by a constant</p> <p>LIMITATIONS: Subjective selection of shape parameter can impact comparability. The index can be relatively insensitive to changes in the middle-range and instead focuses more on the distribution extremes</p>	Evenness	Income	[80]

Table 3 (continued)

Name	Background	Formula	Formula details	Strengths and limitations	Dimension	Domain	References
Absolute Centralization Index	The Absolute centralization index (ACE) captures centralization, it ranges from -1 to 1 with >0 values indicating that minority group members reside closer to the city center, and <0 values indicating that minority group members reside outside of the city center; a value of 0 indicates that the minority group has a uniform distribution throughout the city [18]. ACE can be extended to consider a majority and minority group using the “Relative Centralization Index” (RCE) [18], which describes the share of minority group that would have to change residential areas to match the relative centralization of the majority group; positive values indicate that minority groups live closer to the center relative to the majority group, and vice-versa	$ACE = \sum_{i=1}^m (X_{i-1} A_i) - \sum_{i=1}^m (X_i A_{i-1})$ $RCE = \sum_{i=1}^m (X_{i-1} Y_i) - \sum_{i=1}^m (X_i Y_{i-1})$	X_i = The minority population of areal unit i A_i = The land area of areal unit i Y_i = The majority population of areal unit i M = The number of areal units, ordered by increasing distance from city center	STRENGTHS: Straightforward spatial interpretation. RCE can complement ACE LIMITATIONS: Designed for binary group comparisons. Definitions of “city center” and changes in group categorization may influence results	Centralization	Race	[79]

Table 3 (continued)

Name	Background	Formula	Formula details	Strengths and limitations	Dimension	Domain	References
Correlation Index (<i>Correlation Ratio</i>)	The correlation index measures exposure between minority and majority group members and serves as an adjustment to the “Exposure Index” that accounts for its inherent asymmetry arising from the 2 comparison groups not having the same proportion of group members. The correlation index ranges from 0 to 1, with higher values indicating greater segregation and lower values indicating lesser segregation; a value of 0 indicates complete integration [77]	$\eta^2 = \frac{(I-P)}{(1-P)}$	I = The “Isolation Index” P = Proportion of the total minority population to the total population within an areal unit or study area	STRENGTHS: Accounts for asymmetry between groups and allows for comparisons across different contexts over time LIMITATIONS: Sensitive to group definitions and limited to binary groupings. Does not capture spatial distribution	<i>Exposure</i>	<i>Race</i>	[65]
Local Spatial Segregation Index	The Local Spatial Segregation Index (LSSI) measures the degree to which members of 2 groups are exposed to one another, providing a spatial measure of local segregation. LSSI is calculated for each area to capture the spatial segregation of minority group members from majority group members in a given area [65]. The index ranges from 0 to 1, corresponding to complete integration and complete segregation, respectively. In the case of 2+ comparison groups, LSSI can be easily modified to estimate an overall local value for the population [16]	$S_i = 1 - \frac{(a_i \sum_j c_j b_j) + (b_i \sum_j c_j a_j)}{(a_i \sum_j b_j) + (b_i \sum_j a_j)}$	a = Population count group A in areal unit i b = Population count group B in areal unit i c = The value of cell ij in a spatial weights' matrix, which equals 1 if areal units i and j share a border and zero otherwise (i.e., adjacency matrix)	STRENGTHS: Adjacency matrix accounts for shared borders between areal units which captures the spatial context of neighborhoods. Can handle multi-group comparisons LIMITATIONS: Sensitive to geographic scale and assumes homogeneous areas, which may not accurately represent the complexity of urban structures	<i>Exposure</i>	<i>Race</i>	[65]

deprived social or economic groups (e.g., both tails of a distribution), while composite indices compare social or economic position relative to privilege *or* deprivation (e.g., only one tail of a distribution). Considering these differences, SSP measures were examined separately from composite indices, with findings pertaining to the former displayed in Table 3, and the latter in the Supplementary Materials.

SSP Measures

Our search yielded 18 distinct SSP measures (Table 3) across 7 domains: race, income, race/income, education, language, nativity, and home ownership. A majority of SSP measures focused on race, followed by income, and combined income/race. The domains of education, language, nativity, and home ownership were less frequently utilized.

The most commonly employed SSP measure was the Index of Concentration at the Extremes (ICE), which was used in 37% ($n=43$) of included articles and applied to all of the above domains. The second most commonly employed SSP measure was the Index of Dissimilarity, followed by the Isolation Index, both of which were respectively featured in 18% ($n=21$) and 17% ($n=20$) of the evidence. Additional SSP measures include relative ratios ($n=9$), the Local Getis Ord G^* Statistic ($n=6$), and the Gini Coefficient ($n=4$). SSP measures such as the Location Quotient ($n=3$), Redlining Index ($n=2$), Entropy Index ($n=2$), Delta Index ($n=2$), and the Spatial Proximity Index ($n=2$) were employed by only a handful of studies. Other SSP measures were less commonly employed, including the Exposure/Interaction Index ($n=1$), Kernel Density Estimation ($n=1$), the Atkinson Index ($n=1$), the Krivo Local Isolation Index ($n=1$), the Absolute Centralization Index ($n=1$), the Correlation Index ($n=1$), and the Local Spatial Segregation Index ($n=1$).

SSP Measures of Concentration

The *Index of Concentration at the Extremes* (ICE) was the most frequently employed SSP measure in the body of evidence identified by our review, used in 43 studies. ICE was developed by Massey et al. [19] in 2001 to provide a single summary measure of economic polarization. ICE simultaneously

captures SSP in both deprived and privileged social groups, and ranges from -1 to 1 , where negative values indicate greater deprivation, and positive values indicate greater privilege. More recently, Krieger et al. [26] extended ICE to capture both racial and economic polarization. Since then, ICE has emerged as a leading SSP measure in public health research [120]. Included studies have associated ICE with health outcomes including infant mortality [15, 27–32, 56], cancer [33–39], cardiovascular disease [8, 40, 55], injuries [41, 42, 57], premature mortality [3, 32, 43], and COVID-19 outcomes [58].

The *Location Quotient* measures the relative concentration of minority groups by comparing the proportion of minority group members in a smaller geographic unit (e.g., neighborhood) to the proportion of minority group members in a larger geographic unit (e.g., city). The Location Quotient can take on all non-negative real numbers, with higher values indicating a greater proportion of minority group members in the neighborhood compared to the entire city, and vice-versa. The Location Quotient was used to study breast cancer [109, 110], and colorectal cancer [111].

The *Delta Index* is another relative measure of concentration. The Delta Index ranges from 0 to 1 and represents the proportion of minority group members in a given geographic unit, that would have to move in order to achieve a uniform density across units. Note that this is similar to the evenness dimension, however, given the requisite of information on the land area occupied by each unit, and its explicit focus on density, the Delta Index captures spatial concentration instead of mere evenness. The Delta Index was used in 2 studies on sexually transmitted infections (STIs) during pregnancy [78] and self-rated health [79].

Additional SSP measures of concentration included *Relative Ratios*; a ratio comparing the frequency, probability, or odds of an event between a deprived (i.e., comparison) group and a privileged (i.e., referent) group. Relative Ratios include measures of association common to public health research like the risk ratio, rate ratio, and odds ratio. Relative Ratios range from $-\infty$ to ∞ , and interpretation depends on the choice of comparison and referent group; however, Relative Ratios equal to

1 represent no difference between groups. Relative Ratios were used in 11 studies with various outcomes including non-communicable diseases [92, 93], general physical health [94, 95], and quality of life [44, 96]. The *Redlining Index* is similar to Relative Ratios; however, it measures the odds of mortgage loan denial and follows the interpretation of a pooled odds ratio. The Redlining Index was used in 2 studies on breast cancer survival [112] and pre-term birth [64].

SSP Measures of Evenness

The *Index of Dissimilarity* was the second most frequently employed SSP measure, used in 22 studies. The Index of Dissimilarity is a popular measure of SSP, especially within the domain of racial residential segregation; it ranges from 0 to 1 and represents the proportion of a social group that would need to move across spatial units to achieve a uniform distribution. A Dissimilarity Index with a value of 0 indicates a uniform distribution (i.e., complete integration), and a value of 1 indicates complete segregation [65]. Since its development in 1955 [62], the Index of Dissimilarity has been clearly defined [121], and used in research on cancer [66, 67, 80], cardiovascular disease [68, 69, 81], STIs [70, 78], and obesity [65, 71].

The *Gini Coefficient* is a well-established measure of relative income inequality [122]. The Gini Coefficient indicates how the Lorenz curve, a cumulative frequency distribution, for a specific variable (e.g., income, race) deviates from its uniform distribution [123]. A coefficient of 0 represents perfect equality (i.e., all income is equally shared), and a coefficient of 1 represents perfect inequality (i.e., all income is earned by a single individual) [122]. The Gini Coefficient was used in 4 studies on outcomes including cancer [99], metabolic syndrome [45], and asthma [72], plus STIs [78]. The Gini Coefficient typically provides a summary statistic for a single variable but can be extended to accommodate two variables [98].

The Atkinson Index and the Entropy Index were less frequently used SSP measures of evenness. The *Atkinson Index* is similar to the above measures of evenness, as it was designed to evaluate SSP in terms of relative income inequality. Index values closer to 0 indicate an even income distribution (i.e., integration) and index values closer to 1 indicate an uneven

income distribution (i.e., segregation). The Atkinson Index was recently used in 1 study to examine disparities in colorectal cancer [80]. The *Entropy Index* describes how the racial/ethnic diversity of spatial units within a city differs relative to the diversity (i.e., entropy) of the entire city. A value of 0 represents that all units have the same racial composition as the city, and a value of 1 represents that all units are composed of only 1 group. The Entropy Index was used in studies of self-rated health [79] and body mass index [65]. Both of the above measures include a sensitivity parameter that allows for differential weighting at different points along the distribution.

SSP Measures of Exposure

The *Isolation Index* was designed to measure the degree to which members of a minority group are exposed to other members of the minority group, based on the probability that minority group members share a geographic unit. An index of 0 indicates that a minority group member does not share a unit with another member of the same group, and an index of 1 indicates that the minority group member shares a unit with another member of the same minority group. The Isolation Index was used in 11 studies on cancer [82–84], cardiovascular disease [69, 81, 85, 86], mortality [64, 87], and COVID-19 [88].

The *Exposure/Interaction Index* is another measure of exposure. However, unlike the Isolation Index, the Exposure/Interaction Index describes the probability that a member of the minority group shares a geographic unit with a member of the majority group. This index ranges from 0 to 1, with lower values indicating greater segregation among groups and higher values indicating less segregation between groups. This measure was used in only 1 study which examined the association between the Exposure/Interaction Index and pre-term birth among pregnant women in Philadelphia, PA [64].

The *Krivo Local Isolation Index* encompasses both of the previously described SSP measures for the exposure dimension. The Krivo Local Isolation Index measures the probability of exposure between individuals belonging to 2 social groups compared with what would be expected for the entire city [100]. This index is not bounded between 0 and 1 and can include negative numbers; greater values of the Krivo Local Isolation Index indicate greater separation (i.e., less

exposure/interaction) between the 2 social groups and vice-versa. The Krivo Local Isolation Index was used in 1 study which examined its association with low birth weight among singleton births [101].

The Correlation Index and the Local Spatial Segregation Index were less commonly employed; however, both offer information that is otherwise not captured using the above SSP measures for exposure. Similar to the Exposure/Interaction Index, the *Correlation Index* measures the relative exposure between minority and majority group members but provides an adjustment for the asymmetry inherent to the Exposure/Interaction Index that arises from relative differences in the size(s) of the groups being compared. The Correlation Index ranges from 0 to 1 with greater values indicating a greater probability of exposure between group members. The *Local Spatial Segregation Index* provides a snapshot of local segregation and can facilitate the comparison of more than 2 social groups. An index of 0 or 1 corresponds to the probability that members of the minority group are not exposed to/interacting with members of the majority group. Both indices were used in 1 study on food environments, racial segregation, and body mass index [65].

SSP Measures of Clustering

The *Local Getis-Ord G* Statistic* is a hot spot analysis method used to determine how the racial composition of a geographic unit (e.g., census tract) differs from that of neighboring units (e.g., adjacent census tracts) as compared to the mean racial composition for a larger geographic unit (e.g., city) [102]. The resulting z-scores and p-values guide interpretation with larger z-scores suggesting greater spatial clustering of higher values, and smaller z-scores suggesting greater spatial clustering of lower values. Statistical significance indicates that a unit with higher values is more likely to be adjacent to other units with similarly higher values than would be expected by chance. The Local Getis-Ord G* Statistic was employed in 6 studies on non-communicable diseases [103–106] and general physical health [107, 108].

The *Spatial Proximity Index* is an index designed to measure the spatial clustering of social groups [17]. The index represents the average intra-proximity between a minority group and a majority group, weighted by the proportion of social group members

in the population. Spatial Proximity Index values greater than 1 indicate that minority group members reside closer to other minority group members than majority group members (i.e., greater clustering), and values less than 1 indicate that members of both the minority and majority group reside closer to each other, instead of residing near members of the same group. The Spatial Proximity Index was used in 2 studies on self-rated health [73, 79].

Kernel Density Estimation (KDE) is a method for identifying and mapping hot spots (i.e., clusters) that can be utilized to capture SSP. KDE identifies clustering by continuously applying a probability density function to spatial data and summing results to give a single KDE estimate which can then be used to determine the percent of group members at each population-weighted centroid, effectively providing a measure of clustering for a specified social group [117]. KDE was used in only 1 study on birth outcomes [118].

SSP Measures of Centralization

The *Absolute Centralization Index* was designed to measure how minority group members are distributed around the center of a given city. The Absolute Centralization Index ranges from −1 to 1, with positive values suggesting greater centralization among minority group members, and negative values suggesting lesser centralization (e.g., living further from the city center) among minority group members. The Absolute Centralization Index can be extended to the *Relative Centralization Index* [18], which represents the relative proportion of minority group members that would have to move in order to achieve equivalent centralization with the majority group. The Absolute Centralization Index was used in 1 study on self-rated health [79].

Discussion

In this scoping review, we reviewed evidence on the measurement of SSP and characterized the use of SSP measures in recent public health literature. Results from this review highlight 4 primary findings. First, we found that defining SSP in the context of privilege, deprivation, dissimilarity, and segregation returns a variety of distinct measures, each with

its own interpretation. Second, we found a growing body of evidence that spanned various time periods, geographic settings, and health outcomes. Third, we demonstrated that a majority of SSP measures included in this review can be classified according to Massey and Denton's Dimensions of Residential Segregation, which may ease the interpretability of this literature [18]. Fourth, we found articles with simultaneous attention to multiple SSP measures, as well as those focused on a single SSP measure. Last, we discuss considerations for the application of SSP measures in future public health research, highlighting the strengths, limitations, and contributions of our review.

Our search identified 23 measures overall, 18 of which were distinct measures of SSP, which we classified according to Massey and Denton's dimensions, and 5 of which were composite indices, which are described in the Supplementary Materials. While SSP measures and composite indices are related, these measures differ on the basis of comparison—SSP measures capture both deprivation *and* privilege, while composite indices capture either deprivation *or* privilege, not both. This differentiation is a key element in developing a definition of SSP, which is a critical first step for investigations aiming to examine the impact of SSP on population health outcomes. Here, we propose such a definition of SSP, which requires capturing the relative distribution of the population on *both ends* of a polarized variable.

The majority of included studies were recent and set in the USA, with 44% published between 2020 and 2022 and 88% set in the USA. The most common study designs were cohort studies and cross-sectional studies. Studies included a variety of health outcomes, notably non-communicable diseases, cause-specific and all-cause mortality, general physical health, and maternal and perinatal health. There is a dearth of evidence on SSP and communicable diseases, which is surprising given the emergence of SARS-CoV-2 in early 2020 and the subsequent widening of health disparities across the US [124, 125]. Of the included evidence, only a handful of studies examined COVID-19 outcomes [58, 88, 126], including COVID-19 cases [58, 88], COVID-19 test positivity [58], and COVID-19 mortality [58, 126]. Considering how the COVID-19 pandemic impacted health and health equity [127], investigations featuring SSP may be instrumental in

identifying and addressing the drivers of disparities in COVID-19 outcomes in various geographic units.

Classifying SSP measures according to Massey and Denton's Dimensions of Residential Segregation revealed that concentration and evenness were the most frequently targeted dimensions, followed by exposure, clustering, and centralization. These dimensions were originally posited in Massey and Denton's foundational 1988 manuscript [18], and the identifiability of each dimension was empirically reconfirmed by Massey, White, and Phua in 1996 [128], both of which were most recently discussed by Massey in 2012 [129]. Despite the ability to classify SSP measures using Massey and Denton's Dimensions of Residential Segregation, we acknowledge that SSP is multidimensional in nature. Therefore, in agreement with Massey et al. [128, 129], we recommend that discussions surrounding SSP measurement move beyond those of selecting the “best” or “correct” SSP measure, and instead focus on a multidimensional approach based on several SSP measures.

In terms of the number of SSP measures employed by each study, we found that most studies included a single SSP measure (54.7%), several studies included 2 to 3 SSP measures (36.8%), and only 8.5% of studies included greater than 3 SSP measures. Of the studies that used more than 1 SSP measure, some examined the impact of using several distinct SSP measures, while others employed the same SSP measure across different domains.

Guidance for Researchers

Selecting an SSP Measure

Selecting the appropriate SSP measure for a health study must be informed by the research question. As a multidimensional construct, researchers should identify which relevant dimensions (e.g., Massey and Denton's) and domains (e.g., race, income) of SSP are of interest, to refine measures. Spatial scale matters; for small scales (e.g., census block), measures comparing unit demographics with broader segregation patterns (e.g., Location Quotient) may be preferable to within-unit measures (e.g., ICE). Researchers should also assess whether spatial autocorrelation is relevant, opting for measures leveraging it if needed (e.g., Krivo Local Isolation Index).

Finally, researchers must ensure measures are interpretable for their intended audience.

SSP and Health Research Agenda

First, to move the SSP and health research agenda forward, we argue that a common definition of SSP is needed. Absent this, researchers should explicitly define the SSP motivating their work, using their own or our team's conceptualization. Second, we identified mostly US-based studies, highlighting the need for non-US research to assess the applicability of these measures globally. Third, while we use Massey and Denton's classifications (Table 1) to organize research, a health-focused taxonomy of SSP measures could guide future public health researchers in selecting appropriate measures. Fourth, SSP's multidimensionality spans various domains and dimensions, supporting the use of multiple measures or one measure across domains [130]. Finally, future research should compare results across measures or domains and evaluate how measure selection affects findings [131].

Strengths/Limitations

This scoping review has several limitations and strengths. Regarding limitations, the lack of an established SSP definition made the creation of an effective search strategy difficult. Although we reached a consensus on a definition for SSP while the review was in process, elaboration of a definition in advance may have informed additional terms to include in the search strategy. For example, the inclusion of an independent term for "polarization" may have been useful in identifying studies that employed the coefficient of polarization [132], an existing SSP measure not captured by our review. Additionally, though we did not restrict our search to the USA, our search strategy used US-based terms (tract, county, etc.), using more inclusive geographic terminology could have broadened our search strategy to capture more non-US studies. Regarding the strengths of this study, our scoping review provided a novel characterization of SSP measures and their application(s) in recent public health literature. We reviewed each SSP measure, compared measures in terms of their strengths and limitations, and provided tabulated results; all of which can help researchers navigate options for

measuring SSP, and guide the selection of SSP measures for use in public health research.

Conclusion

We conducted this scoping review to guide in the selection and application of SSP measures in public health research. We identified several unique SSP measures, their respective methods, and domains, and summarized their use in recent public health literature since 2007, filling a critical gap in the literature. Our findings draw attention to the benefits and pitfalls of each SSP measure and explore methodological options for measuring SSP in public health research. We also provide what we understand to be the first, provisional definition of SSP in the context of public health and highlight the importance of such a definition. Finally, aside from the resources offered in this review, the author team has developed the Spatial Social Polarization Database [133], an online application and interactive mapping tool, that can be used to examine select SSP measures, like ICE, at various geographies (https://drexel-uhc.shinyapps.io/SSP_Maps/), with a public repository [134]. We encourage researchers to leverage our findings and resources to better understand the role of SSP measurement in public health research, especially in the modern presence of both new and re-emerging health disparities.

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Data Availability The data that support the findings of this study are available from the corresponding author, EMM, upon reasonable request.

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