Neighborhood Deprivation as a Measure of Social Need and Healthcare Utilization: A Review of the Literature

by

Lisa M. George

BA, English Literature, University of Pittsburgh at Johnstown, 1990

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This essay was submitted

by

Lisa M. George

on

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and approved by

Essay Chair:
Mary Hawk, DrPH
Associate Professor and Associate Chair for Research
Behavioral and Community Health Sciences
Graduate School of Public Health
University of Pittsburgh

Essay Reader:
Thuy D. Bui, MD
Associate Professor of Medicine
Division of General Internal Medicine
Department of Medicine
University of Pittsburgh

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Abstract

Social and material deprivation at the individual level has a well-documented relationship with increased risk for poor health outcomes and use of high-cost healthcare services. Unmet social needs, such as reliable transportation, access to nutritious foods, safe and stable housing, ability to pay household utilities, and personal safety, can affect individuals' overall health status. However, the greater context in which people live also can have a significant impact on both health and healthcare utilization. Neighborhood-level deprivation can affect the physical and emotional well-being independent of residents' individual socioeconomic status and can perpetuate the health inequities that exist in the United States. Longstanding structural factors have contributed to these inequities, and they are manifested in the form of reduced access to preventive care and chronic disease management.

Given the intrinsic link between unmet social needs and poor health, efforts to identify methods for addressing these needs are of great public health significance. Social needs screening in the clinical setting is not widely performed despite the benefit that information on unmet needs could provide in developing a plan of care. One promising strategy to address health disparities and unmet social needs is the use of geographic-based indices to identify and address deprivation at the neighborhood level. Such measures have been used outside of the United States to allocate funding to healthcare facilities, inform community needs assessments, and guide health policy with the ultimate goal of addressing disparities in population health. To gain an understanding of the utility of deprivation indices as predictors of healthcare outcomes and healthcare utilization in the United States, a review of the literature was conducted. Twelve studies were identified that developed and used several different neighborhood-level deprivation scales to assess healthcare utilization, chronic disease management, and mortality. Results of this review showed that measures of deprivation at the neighborhood level were effective predictors of poor health outcomes in the populations and geographic areas studied, and this information could be a useful adjunct to patients' health records. The strengths and limitations of these studies as well as recommendations for further research are provided in this analysis.

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Preface

I became acquainted with the concept of neighborhood deprivation as a measure of social needs while completing a practicum under the direction of Dr. Thuy Bui at UPMC. In analyzing patient data collected through Dr. Bui's Social Needs Action Program to track readmission rates for patients within low–socioeconomic status zip codes, I developed a curiosity about how the healthcare setting can more effectively address the social determinants of health and the variability that exists in access to care and health outcomes. I appreciate the insight that Dr. Bui shared with me and her input as a reader for this essay.

As an instructor and academic advisor, Dr. Mary Hawk has provided inspiration and guidance to me over the past year as well as thoughtful suggestions for refining this essay. I am eternally grateful for Dr. Hawk's insight and support and for sharing her passion for health equity and looking at public health issues through a harm reduction perspective.

I extend sincere appreciation to Dr. Steven Albert for facilitating my practicum work with Dr. Bui and for enabling me to remain engaged in his ongoing social needs screening research. Special thanks go to Dr. Jeanette Trauth, who provided guidance and advisement as I began my public health education. To my former classmates—and now valued friends—Julie Brewer and Terri Pacella, I am so grateful to have met and worked with such talented, strong women through all of the challenges and achievements during our time together at Pitt.

Finally, I could not have completed this endeavor without the unending support of Ben Becze. From lending a sympathetic ear as I prepared to apply to the program in 2016 through completion of my studies, Ben's continued encouragement and wholehearted faith in my abilities have given me the strength to continue in this journey, and his motivational messages before every single class through eight semesters have inspired me to face each challenge along the way. I am forever grateful.

1.0 Introduction

The benefits of identifying patients with unmet social needs within the healthcare setting are being increasingly recognized as contributing to improved patient outcomes (Gold & Gottlieb, 2019). Lack of access to transportation, food insecurity, housing instability, lack of household utilities, and interpersonal violence can have an effect on patients' hospital readmission rates, treatment adherence, and overall health status. Deprivation can exist at both the individual and population levels. Liaw et al. (2018) found that census tracts with lower income and education levels and higher levels of social deprivation are associated with worse outcomes related to chronic conditions. Data on patient-level socioeconomic statuses, however, are consistently lacking in electronic health records. Social needs screening in the clinical setting, which has been recommended by organizations such as the American Academy of Family Practitioners and National Association of Community Health Centers, is not widely performed. A cross-sectional study performed by Fraze et al. (2019) found that only 16% of physician practices and 24% hospitals conduct screening of patients for social needs. Tools such as the Accountable Health Communities Health-Related Social Needs Screening Tool (Centers for Medicare and Medicaid Services, 2018) enable collection of data on social determinants such as housing insecurity, hunger, and interpersonal violence during a clinical encounter. Identification of unmet social needs is an important step in developing effective interventions to address the social determinants that impact both health outcomes and healthcare costs. These needs exist at both the individual and community levels.

Neighborhood characteristics contribute to the health of individuals who reside in the community in multiple interrelated ways, and these characteristics also can perpetuate inequities in heath (Diez Roux & Mair, 2010). Understanding the context in which people live can provide insight into the factors that contribute to health beyond individual behavioral and genetic factors. Measures such as area deprivation index, which provides a score that allows comparison of neighborhood characteristics related to economic disadvantage and access to resources, are being studied as ways to better identify which patients may benefit from social needs intervention and have demonstrated some success (Hu et al., 2018). Deprivation scales also are being studied to determine the impact of neighborhood factors on healthcare utilization and repeat hospitalizations.

This project is aimed at examining existing research on the utility of geospatial indices to identify populations residing in areas with characteristics of deprivation who may have unmet social needs that could negatively impact their health outcomes and care utilization. It will begin with an overview of how the social environment impacts health. Then it will explore how unmet social needs contribute to clinical outcomes and introduce the concepts of neighborhood deprivation indices, including their background, implementation outside the United States, and factors contained in the currently used indices. Next, this paper will examine the existing research into the development and use of several different deprivation indices in the United States for clinical and population-based assessment, including the variables examined and geographic scales used, as well as the health-related conditions and types healthcare utilization being studied. Potential uses for deprivation indices discussed in the literature will be explored, including incorporation of neighborhood-level data into electronic health records (EHRs) for individual and population risk assessment. This paper also will discuss the limitations of and gaps in the existing literature.

The widespread incorporation of neighborhood-level deprivation scales has the potential to reduce healthcare costs associated with inadequately managed chronic conditions, emergency department visits, and repeat hospital admissions by identifying the neighborhood-level factors that are contributing to healthcare utilization and poor outcomes. Availability of these data to providers at the point of care may facilitate social needs screening within the clinical care setting by providing a mechanism for identifying individuals who may be at greater risk of having unmet needs. This may enable providers to connect patients with community resources and services to aid with addressing these unmet needs. It also may help to inform the implementation of community programs and interventions by taking into account the neighborhood-level factors that must be considered during program design and development. The characteristics of one's neighborhood can perpetuate inequalities in access to services and resources. The ability to identify and address disparities at the neighborhood level may ultimately lead to greater equity in health policy and care delivery. As noted by Wizdom Powell, PhD, Director of the Health Disparities Institute and Associate Professor of Psychiatry at UConn Health, when individuals experience premature mortality from preventable conditions, both the family and the entire community are impacted and diminished by the loss (Headspace, 2020).

1.1 Purpose of Research

The circumstances in which people live can have a marked impact on health (Commission on Social Determinants of Health, 2008). Social determinants such as food insecurity, housing instability, ability to pay household utilities, transportation needs, and interpersonal violence are commonly viewed within the context of the individual. However, these factors also exist at the neighborhood level in ways that impact population health. The neighborhood can directly affect individuals' access to health-supporting amenities and social interactions, as well as their stress level and personal safety (Kind & Buckingham, 2018). National organizations focusing on healthcare quality have recommended that data on social determinants be included in patients' EHRs (Hughes et al., 2016). Having data on such factors that exert influence on the individual's health available at the point of care could provide clinicians with a broader perspective of the external conditions that may affect patient health and influence the delivery of more personalized care. However, screening for and incorporation of social determinants of health (SDOH) data into patient records is not widely performed. Reasons for this include the complexity and time-consuming nature of obtaining such data from patients during a clinical encounter, as well as the associated costs with implementation, patient reluctance to divulge such information, and lack of resources available to clinicians to address patients' identified needs, such as social work referrals. Researchers are examining methods for estimating deprivation at the neighborhood level in an attempt to more effectively and efficiently identify and address factors that may be contributing to increased healthcare utilization and poor health outcomes. This could benefit patients' clinical outcomes and inform development of community-based health interventions, as well as reduce expenditures for providers. The purpose of this project is to synthesize the current literature on the development and utility of neighborhood-level deprivation indices as proxies for individual-level data on unmet social needs and healthcare utilization.

1.2 Background

1.2.1 Social Environment and Health

The World Health Organization (2020) defines SDOH as "the conditions in which people are born, grow, live, work and age." The inextricable connections among income, education level, food security, interpersonal violence, housing conditions, access to transportation, social interactions, and health have been well-studied at both the individual and population levels. The impact of social determinants is notable in the health disparities that exist among individuals of minority racial and ethnic groups and those of low socioeconomic status (Kind & Buckingham, 2018). Despite our collective understanding of the connections between social environment and health, the U.S. healthcare system still fails to incorporate effective interventions for addressing these disparities. The United States spends far more on health care than other wealthy countries, yet health outcomes for patients in the United States remain worse (Institute of Medicine & National Research Council, 2013). The fee-for-service model incentivizes diagnosis and treatment over prevention, but progress is slowly being made toward adopting a fee-for-outcomes model.

At the policy level, attention is beginning to be directed toward strategies promoting more equitable health access and improved outcomes. Healthy People 2020 incorporated an ecological approach that "focuses on both individual-level and population-level determinants of health and interventions" (Office of Disease Prevention and Health Promotion, 2020). The Centers for Medicare and Medicaid Services is addressing SDOH6y and advocating for screening in the healthcare setting through initiatives such as its Accountable Health Communities Model and Health-Related Social Needs Screening Tool and the incorporation of "Z" codes in the International Classification of Diseases-10-CM (ICD-10-CM), which provide a standardized system to enable providers to capture patients' socioeconomic and psychosocial needs during a clinical encounter (James, 2019). Despite the introduction of Z codes in the ICD-10-CM upon its release in 2015, a study of Medicare fee-for-service patients showed that Z codes were recorded for less than 1% of this population (Weeks et al., 2020). The Institute for Healthcare Improvement developed the "Triple Aim" framework in 2007 as a focus for improving the performance of health systems through increasing quality of care and patient satisfaction, improving population health, and decreasing healthcare costs (Institute for Healthcare Improvement, 2020). Despite the promise that this framework provided for reducing health disparities, the institutional focus on controlling costs has hindered progress toward achieving the intended care-focused goals (Wilkinson et al., 2017). From a policy perspective, efforts are being made to address the impact of social determinants on healthcare outcomes, resource utilization, and costs. However, widespread implementation of measures to assess for and intervene on the multiplicity of factors that impact individual and population health has yet to be achieved. The Patient Protection and Affordable Care Act (2010) has increased access to healthcare for millions by reducing barriers to obtaining health insurance, yet disparities in health still persist, speaking to the complex, multidimensional nature of health. Health inequities also have huge financial costs: as noted by Artiga, Orgera, and Pham (2020), 30% of healthcare costs for people of color are associated with health inequities. Access to care and insurance alone cannot amend the disparities that are deeply rooted in geographic, social, and structural factors.

1.2.2 Epidemiology of Social Determinants of Health

Research has consistently demonstrated a link between SDOH and chronic disease and other negative health outcomes, including diabetes, cancer, cardiovascular disease, poor maternal and child health outcomes, and obesity (Amjad et al., 2019; Arroyo-Johnson & Mincey, 2016; Coughlin, 2019; Havranek et al., 2015; Walker et al., 2014). These determinants exist at both the individual and population levels. Individual-level factors include race, gender, education level, social support, and socioeconomic status. At the population level, health among communities is impacted by an array of factors, including safe and affordable housing, reliable transportation, quality healthcare, nutritious foods, and neighborhood characteristics.

From an epidemiologic perspective, disease causation, particularly in the case of chronic disease, involves a complex interplay of genetic, behavioral, and environmental factors. Many of these can be linked to neighborhood characteristics that influence SDOH and must be untangled to understand the “reciprocal causation” and develop truly effective methods for assessing and intervening to improve health (Diez-Roux, 1998). For example, consistent consumption of a diet consisting primarily of foods of low nutritional value can lead to development of diabetes or other health concerns. Recommending that an individual make dietary modifications is sound medical advice. However, if neighborhood access to healthful foods is limited, and if an individual lacks a personal vehicle and the nearest supermarket is several public transportation routes away, additional interventions are needed to address the layers of causation. Similarly, cardiovascular disease can be associated with a lack of physical activity, but an individual who works irregular hours or multiple jobs to maintain household expenses may be challenged to adopt a walking program for health if living in a neighborhood that lacks sidewalks for safe outdoor walking or poses a threat to personal safety because of crime rates in the area. Figure 1 illustrates the multiple and interrelated factors that contribute to health over the life span (Institute of Medicine, 2000)

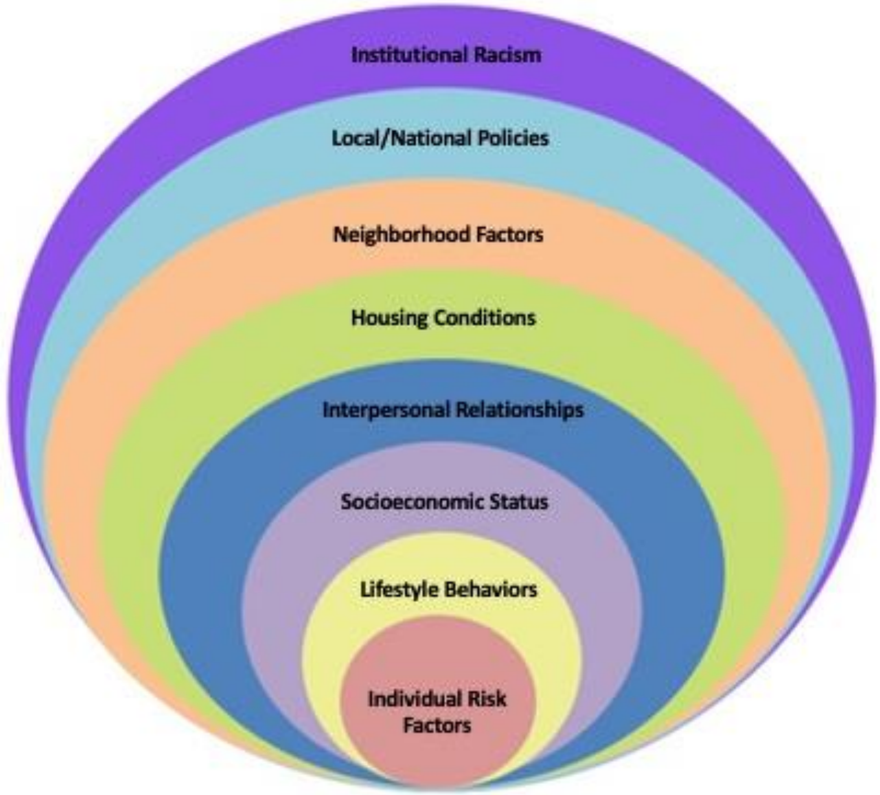

Figure 1 Multiplicity of Factors That Impact Health Across the Lifespan (adapted from institute of Medicine, 2000)

Individuals' health is impacted by wide-ranging life experiences, social interactions, structural factors, and institutional and policy forces, many of which can leave people vulnerable to living situations that do not support physical and mental well-being. This can lead to chronic illness, increased healthcare utilization, poor management of health conditions, and increased mortality. These factors extend across the lifespan and affect generation after generation, perpetuating inequities in health and quality of life. Of particular note is that neighborhood-level socioenvironmental characteristics are linked to mortality; as noted by Kaplan (1996), this link is "independent of characteristics of the individuals, and . . . personal and socioenvironmental risk factors cluster together in areas of low income and high mortality" (p. 507). Researchers are increasingly examining the interplay of neighborhood characteristics and social deprivation and the ways in which these neighborhood-level factors contribute to health outcomes, and this interplay will be explored throughout this paper.

1.2.3 Unmet Social Needs and Clinical Outcomes

The importance of identifying unmet social needs within the healthcare setting is being increasingly recognized by providers and professional medical associations as contributing to improved patient outcomes. Conducting screening for unmet needs and referring patients to resources in their communities has been shown to reduce patient readmission rates, improve outcomes, and decrease healthcare utilization (Bui et al., 2020; Fraze et al., 2019; Gold & Gottlieb, 2019). Commonly used patient information management systems incorporate SDOH modules that can be employed to document data obtained through social needs screening during clinical encounters. Yet, incorporating social needs screening into healthcare practices and EHRs is not widespread among healthcare practices (Fraze et al., 2019). Readmission rates are one measure of healthcare quality and can affect levels of reimbursement for care, but these readmissions may be more a reflection of patients' neighborhood condition than the quality of care provided (Singh & Lin, 2019). Factors contributing to this lack of screening in the clinical setting include time constraints, lack of reimbursement, and the ethical concern of being unable to adequately address patients' identified needs, whether as a consequence of limited availability of social services in the community or lack of clinician knowledge of the relevance of unmet needs to health. In addition to practitioner-related barriers to screening, researchers have explored acceptability of social needs screening to patients in the clinical setting. Although patients indicate that they find screening for social needs to be appropriate in the medical setting, they also express concerns about privacy and confidentiality, as well as some resistance to incorporating social needs data into EHRs (Byhoff et al., 2019; De Marchis et al., 2019). These barriers to widespread incorporation of social needs screening in the clinical setting have led researchers to explore alternatives to obtaining social needs data directly from patients. Methods involving examination of inequalities in health and disease from a geospatial perspective are gaining increased attention for their ability to serve as a proxy for direct assessment of social deprivation for patients. Such methods also have the potential to inform public health programs and interventions by targeting neighborhood-level factors that are influencing individuals' ability to adopt behaviors that lead to improvements in health and well-being.

1.2.4 The Use of Neighborhood Deprivation Indices

Researchers have been exploring methods to more effectively identify populations at increased risk for unmet social needs and poor health outcomes based on the characteristics of their neighborhood environment; among these are social deprivation indices used to serve as proxies for socioeconomic data obtained directly from patients. The characteristics of the neighborhood environment may potentially serve as a suitable alternative for individual socioeconomic characteristics to predict social needs.

The concept of measuring neighborhood-level deprivation has become widely accepted outside of the United States. As noted by Phillips et al. (2016), the United Kingdom and New Zealand have constructed indices based on census and other available data to measure differences in socioeconomic factors at the community level. These indices are being used in research, community needs assessment, health policy, and allocation of funding for clinical care with the aim of ultimately addressing disparities in population health. Research conducted outside of the

United States has examined links between neighborhood-level deprivation and a variety of health conditions. These include diabetes (White et al., 2016), mental health (Weich et al., 2005; Zammit et al., 2010), cardiovascular disease (Winkleby et al., 2007), and maternal and child health (Zeitlin et al., 2011). The United Kingdom and New Zealand have established neighborhood-level deprivation indices that are used to inform allocation of healthcare funding and development of community resources to address disparities (Phillips et al., 2016). The concept of using deprivation indices to inform healthcare systems on strategies to reduce healthcare utilization may be unique to the United States as a result of its fee-for-service system, which differs from care delivery models elsewhere in the developed world.

Despite the persistent disparities that exist in health among the population, the United States has not broadly adopted use of neighborhood-based indices to address patterns of deprivation. Singh (2003) introduced a deprivation index for the United States in an effort to approximate the living conditions that exist in all U.S. counties. A range of 17 socioeconomic indicators were drawn from U.S. Census data and included relative income, education, occupations, levels of unemployment, housing costs, number of members of a household, percentage of English-speaking residents, access to transportation, and basic household utilities. More recently, work undertaken by researchers at the University of Wisconsin School of Medicine and Public Health (2015) has led to the development of The Neighborhood Atlas, a website that provides access to on-demand area deprivation index (ADI) scores, as well as maps and downloadable data based on the work of Singh (2003) and Kind et al. (2014). The intent is to allow information compiled on deprivation—defined as a composite of domains consisting of income, education, housing quality, and employment—at the neighborhood level to be readily available for use in developing interventions and policies in the healthcare, governmental, and public health settings to better target the needs of the population served, particularly those of greater disadvantage. Evaluating social determinants at the population level can provide a crucial first step toward gaining a greater understanding of the context in which people live and the multitude of factors that contribute to healthcare outcomes and utilization of care. This can drive the development of more focused and effective community-based programs and interventions designed to address the particular unmet needs within a given geographic area. The potential also exists, as will be discussed later in this literature review, for ADI and other neighborhood deprivation indices to better personalize care provided in the clinical setting. The incorporation of neighborhood deprivation scores into patients' EHRs could serve as a prompt for clinicians to conduct social needs screenings as well as to facilitate referral to social work services and connection to resources within the patients' local community to address unmet needs. Given the challenges associated with implementing universal social needs screening, having a mechanism to identify patients who may benefit from screening could facilitate incorporation of such screening into clinical care.

The ADI that forms the foundation of The Neighborhood Atlas is provided in rankings from 1 to 100 for the national level and from 1 to 10 for state use, with lower score indicating lower level of deprivation for the designated area. Figure 2 provides an example of a mapped area in Allegheny County in Western Pennsylvania and its associated ADI score. In this example, the state decile score of 10 indicates that this is an area reflecting the highest level of deprivation.

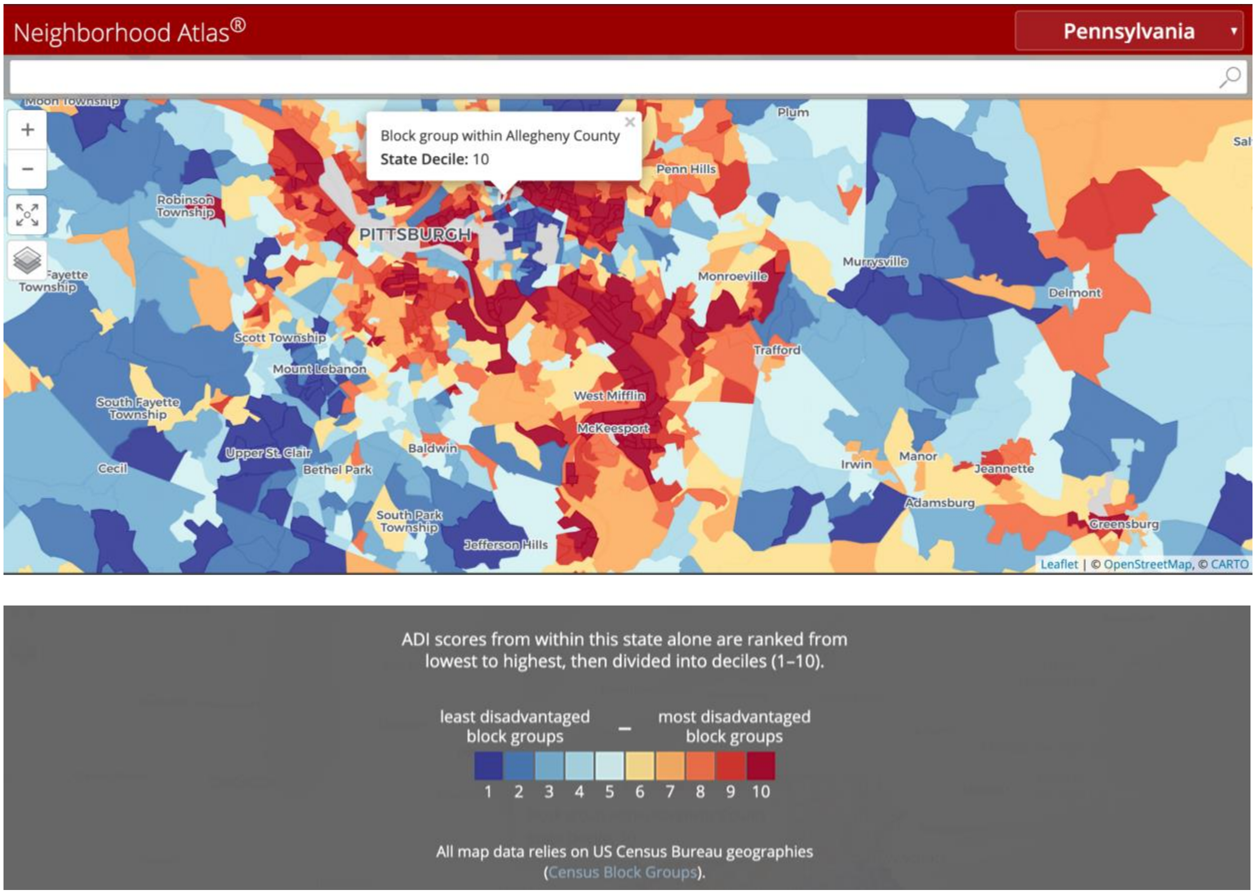

Figure 2 Snapshot of Area Deprivation Index Map From the Neighborhood Atlas

1.3 Research Objectives

As noted previously, the poor health outcomes experienced by individuals in the United States relative to the rest of the world belie the level of healthcare spending in this country. Increased attention is being paid to addressing SDOH, but cohesive strategies to effect change are limited. Quality improvement initiatives are gaining traction in the clinical setting, with social needs screening being considered to address nonmedical concerns that may be impacting healthcare utilization and outcomes. The barriers to widespread screening, however, speak to the need to explore alternative methods for identifying and addressing unmet needs. The use of neighborhood-level deprivation indices throughout the world as proxies for obtaining individual-level data on social determinants has shown promise. Whether this strategy can achieve improvements in population-level health in the United States remains to be seen.

The objectives of this paper are to synthesize the existing literature in an effort to achieve the following:

1. Identify different methods in use for assigning neighborhood-level deprivation classifications within the United States
2. Identify potential improvements in health outcomes and healthcare spending through use of neighborhood-level deprivation indices

2.0 Methods

Prior to conducting a literature search, a list of key terms was generated from the research question: Are neighborhood-level factors effective predictors of unmet social needs in U.S. adults? Primary terms included “neighborhood deprivation” and “unmet social needs.” Synonyms were identified for these concepts to broaden the search. Searches of the key concepts were performed using the National Library of Medicine’s PubMed database as well as the Google Scholar database. Results of these database searches are included in Tables 1 and 2. Articles that focused on populations with specific disease conditions were excluded. To supplement the literature identified through these database searches, additional articles identified via prior research into neighborhood deprivation and social needs were included and also served as a source of additional keyword search terms and MeSH tags. Additional relevant literature was located through snowball searching using the “Similar Articles” and “Cited By” features included in the PubMed record of key articles identified for inclusion.

2.1 Inclusion Criteria

The literature selected for this review was restricted to the time period of 2005 through 2020. Only English-language articles were included. The concept of neighborhood deprivation indices was found to be more commonly in use in countries outside the United States, but given the scope of this paper, the literature pertaining to research conducted outside the United States was consulted for background information on the concept but excluded from the final literature review. Additional studies that focused on the impact of unmet social needs on health outcomes were excluded from the literature review but were used to provide context for this project in the Background section.

2.1.1 PubMed

The PubMed search yielded wide-ranging results based upon the combinations of keywords and MeSH terms included. The most relevant results were obtained from the combinations of "area deprivation index" OR "neighborhood deprivation" AND "social needs screening," which yielded 41 results; and "area deprivation" OR "neighborhood deprivation" AND "unmet social needs," which yielded 25 results, both filtered to the 2005–2020 publication period.

Table 1 PubMed Search Terms

Search number	Query	Filters	Results
1	area deprivation index	–	3,116
2	neighborhood deprivation	–	2,645
3	social needs	–	103,181
4	area deprivation	–	18,917
5	residence characteristics[MeSH Terms]	–	65,201
7	healthcare disparities[MeSH Terms]	–	16,838
8	(((area deprivation index) OR (neighborhood deprivation)) AND (social needs)) AND (healthcare disparities[MeSH Terms])	–	12
9	social needs screening	–	16,322
10	neighborhood socioeconomic factors	–	26,873
11	unmet social needs	–	3,304
12	((area deprivation) OR (neighborhood deprivation)) AND (unmet social needs)	–	31
13	((area deprivation) OR (neighborhood deprivation)) AND (unmet social needs)	2005–2020	25
14	((residence characteristics[MeSH Terms]) AND (healthcare disparities[MeSH Terms])) AND (unmet social needs)	–	7
16	community-level social data	–	1,451

17	(community-level social data) AND (((area deprivation) OR (neighborhood deprivation)) AND (unmet social needs) AND (2005:2020[pdat]))	–	0
18	((neighborhood socioeconomic factors) OR (community-level social data)) AND (unmet social needs)	–	87
19	((area deprivation index) OR (neighborhood deprivation)) AND (social needs screening)	–	54
20	((area deprivation index) OR (neighborhood deprivation)) AND (social needs screening)	2005–2020	41
21	area deprivation index	2005–2020	2,599
22	(social needs screening) AND (residence characteristics[MeSH Terms])	–	361
23	(social needs screening) AND (residence characteristics[MeSH Terms])	2005–2020	307

2.1.2 Google Scholar

A Google Scholar database search was performed using the terms “area deprivation index” and “neighborhood deprivation.” The search was limited to articles published between 2005 and 2020. Results of these two database searches were compared and cleaned for duplications before reviewing articles for inclusion.

Table 2 Google Scholar Search Terms

Query	Results
“neighborhood deprivation”	5,160
“neighborhood deprivation “United States”	3,760
“area deprivation”	9,610
“area deprivation” “United States”	4,260
"area deprivation index"	774
"area deprivation index" “United States”	427
"area deprivation index" "United States" "unmet social needs"	4
"neighborhood deprivation" "United States" "unmet social needs"	12
"neighborhood deprivation" "United States" "social needs screening"	6
"area deprivation" "United States" "social needs screening"	6

2.2 Study Selection

For this review, papers meeting the inclusion criteria were evaluated to identify those that explored the development and use of neighborhood deprivation indices in the United States. In addition, research studies that used these indices to test their ability to identify the effect of neighborhood deprivation on healthcare utilization or health outcomes were selected for review. A total of 12 articles that met the defined criteria were identified for this review. Additional studies were found that examined the effect of area deprivation on specific health-related concerns, but these were beyond the scope of this paper and thus not included. Of note is the relative recency of the selected papers. Even given the literature search parameter of 2005–2020 publication date, the majority of the selected papers were published after 2015, suggesting an increased interest among researchers in exploring the topic of neighborhood-level factors as influencers of health for use in healthcare quality improvement initiatives.

3.0 Results

A comprehensive review of the 12 articles revealed a multiplicity of approaches to the use of geospatial factors to identify patients residing in areas of deprivation. Several deprivation indices were used. Likewise, the geographical scope for analysis varied among studies. Overall, researchers found that geography-based measures of deprivation demonstrated association with outcomes of interest, whether specific health conditions or healthcare utilization.

A summary of the studies reviewed and their overall objectives, methods, and results appears in Table 3. Additional analysis of the literature will be provided in subsequent sections.

Table 3 Summary of Literature Search Results

Study	Objectives	Methods	Results
Bhavsar et al. (2018)	To determine if neighborhood socioeconomic status (nSES) has utility in predicting adverse health outcomes beyond information already contained in the electronic health record (EHR)	Cohort study of 90,097 patients 18 years or older who had at least one health encounter in Durham County, NC Used the Agency for Healthcare Research and Quality's socioeconomic status index to calculate an nSES index and supplemented EHR data with data from the American Community Survey	An association was found between nSES and patient health, with the predictive value varying by outcome of interest. When added to EHR variables, nSES did not enhance the predictive value for any health outcome, so the EHR data itself could be more effectively utilized to predict likelihood of health adverse health outcomes.
Butler et al. (2013)	To develop a multidimensional social deprivation index to measure healthcare access and health outcomes within a small geographic area	Selected variables for social deprivation via literature review and existing international indices Conducted correlation and multivariate analyses with the developed deprivation index and measures related to healthcare outcomes and healthcare system access and compared the index with the single variable of poverty	The index demonstrated a positive association with poor access and poor health outcomes. The multidimensional deprivation index had a stronger association with health outcomes than did poverty alone.
Carlson et al. (2020)	To compare the effectiveness of neighborhood stress score (NSS) and area deprivation index (ADI) in identifying relationships between socioeconomic risk and utilization of acute healthcare services NSS and ADI use different Census indicators (7 indicators versus 17, respectively).	For patients at two academic medical centers in Boston, conducted regressions analyses of ADI and NSS deciles with counts of emergency department visits, hospital admissions, and repeat emergency department visits	Both indices demonstrated effectiveness in assessing socioeconomic factors that potentially impact potentially preventable healthcare encounters. The NSS decile had a greater effect size for all of the healthcare utilization measures, so it may be a more effective tool for developing programs that address social determinants at the geographic level.
Chamberlain et al. (2020)	To assess whether ADI is associated with multimorbidity after adjusting for socioeconomic status for adults residing in 7 counties in Minnesota	Using a cross-sectional design, obtained prevalence of 21 chronic conditions and calculated proportion with 2 or more chronic	After adjusting for age, sex, race, and ethnicity, individuals in the lowest ADI quintile had a 50% increased risk of multimorbidity and a 67% increased risk of

Study	Objectives	Methods	Results
		conditions as well as those with severe multimorbidities ($\geq$ 5 chronic conditions) Estimated ADI for the population-based sample at the census block group level and obtained odds ratio for the association of ADI with multimorbidity and severe multimorbidity	severe multimorbidity compared to those in the highest ADI quintile. Adjusting for education level demonstrated an even stronger association.
Durfey et al. (2019)	To examine the relationship between ADI and management of several chronic conditions among Medicare Advantage patients	Performed secondary analysis of Medicare Healthcare Effectiveness Data and Information Set, Medicare enrollment data, and ADI (developed by Kind et al., 2014) to test association of ADI with health outcomes, adjusting for geographic and individual factors Used ZIP+4 for residence location, which can be linked to Census block groups	Medicare Advantage patients in the highest ADI groups were less likely to have controlled blood pressure, diabetes, and cholesterol, demonstrating that ADI could be an effective tool for tracking disparities in management of chronic conditions.
Hu et al. (2018)	To evaluate the effect of neighborhood characteristics on patients' risk of readmission when controlling for other risk factors	Performed multivariate regression analysis for readmissions (drawn from Centers for Medicare and Medicaid reporting) and ADI score as refined by Kind and colleagues at University of Wisconsin School of Medicine and Public Health Extracted patient demographics from hospital-provided data and geocoded addresses to census block groups to assign an ADI to each patient	Regression analysis showed that patients living in the top 5% most disadvantaged neighborhoods were 70% more likely to experience a readmission as compared to patients residing in less-disadvantaged neighborhoods.
Kind et al. (2014)	To examine whether a relationship exists between Singh's (2003) ADI and 30-day rehospitalization rates	Conducted retrospective cohort analysis using a random sample of Medicare patients with diagnoses of congestive heart failure, pneumonia, or myocardial infarction and multivariate logistic regression of ADI and rehospitalizations	Individuals living in the 15% most disadvantaged neighborhoods had 30-day rehospitalization rates of 22%–27%, whereas rates for the 85% least disadvantaged averaged 21%, with little variation across ADI in this group.

Study	Objectives	Methods	Results
			Findings confirm a threshold effect, in which there exists a point beyond which increases in disadvantage lead to increases in poor health outcomes.
Knighton et al. (2016)	To examine the calculation of an ADI for the state of Utah to use as a proxy for data collection at the point of care as part of a quality improvement initiative for Intermountain Health in Salt Lake City	Identified a cohort of patients receiving treatment from 1994–2015 and associated their addresses with a block group Used the University of Wisconsin School of Medicine and Public Health ADI coefficients as a basis for the Utah ADI Calculated base score for each census block group then standardized the base scores for each block group using Utah population mean base score and standard deviation	The Utah ADI demonstrated substantial difference between the least deprived and most deprived quintiles, suggesting that material deprivation may have a meaningful impact on population health and may have broad applicability for use in a health system to address the effect of social determinants in their patient population. Use of data at the census block group–level was more effective at identifying the impact of social determinants than use of ZIP code or census tract
Kolak et al. (2020)	To examine how social determinants of health vary across geographic areas and to specifically explore their association with mortality rates in Chicago	Using a cross-sectional design, developed social determinants indices based on census tracts within the continental United States and used these indices to estimate age-adjusted mortality within census tracts in Chicago Selected 15 variables to characterize social determinants of health and reduced these to 4 indices to reflect advantage, isolation, opportunity, and mixed immigrant cohesion and accessibility; clustered these into 7 neighborhood types and conducted a regression analysis to estimate premature mortality within the neighborhood clusters	All social determinant indices were associated with age-adjusted premature mortality rates. Results using Chicago as a case study were consistent with other research by Singh et al., which indicated that poverty may account for nearly half of the variance observed in health outcomes.
Liaw et al. (2018)	To identify the relationship between "cold spots" and clinical outcomes related to	Conducted a cross-sectional study of patients in 12 practices in 5 affluent counties in northern	Other than aspirin use, all other health factors were influenced by living in a cold spot.

Study	Objectives	Methods	Results
	five health factors: obesity, uncontrolled diabetes, pneumonia vaccination, cancer screening, and aspirin use	Virginia using EHR residential address data geocoded to census tracts Identified "cold spots" through use of American Community Survey data, the SDI described by Butler et al. (2013), and life expectancy data from Virginia Conducted bivariate and logistic regression analysis on the census tracts in the worst quartiles	Substantial variation was seen across the practices in the proportion of patients living in more deprived communities.
Maroko et al. (2016)	To refine the ADI developed at the University of Washington and test the strength of association with health outcomes in an 8-county region of New York State.	Averaged data on hospitalizations for patients from 1999 through 2001 to match 2000 ADI data Assessed variability between the 15% highest deprivation areas and the 85% lowest deprivation areas as described by Kind et al. (2014) for their association with rehospitalization rates	This locally adjusted ADI demonstrated a stronger association with health outcomes than ADIs using a larger geographic area, suggesting that more regional approaches to assessing deprivation should be considered for use by health systems.
Xiao et al. (2017)	To examine the association between neighborhood socioeconomic deprivation and the risk of developing fair or poor self-rated health when reporting baseline health of good or better and to evaluate how individual-level risk factors influence the effect of neighborhood socioeconomic deprivation	Conducted a large cohort study of middle-aged and older adults over a 10-year period with participants in the NIH-AARP Diet and Health study Geocoded addresses and linked to census tracts and used a method described by Messer et al. (2006) to generate a neighborhood deprivation index using 10 variables Respondents rated their overall health as excellent, very good, good, fair, or poor, and statistical analyses were performed to correlate self-reported health status with neighborhood deprivation score.	Living in more a deprived neighborhood was a strong predictor of self-reporting health as poor or fair over the follow-up period. The association was only partially explained by factors such as socioeconomic status, health behaviors, and disease conditions.

3.1 Deprivation Indices Used

As previously noted, the United States has not established a standard index for measuring deprivation at the neighborhood level, in contrast with other countries across the globe. Several of the studies found through the literature search endeavored to establish a deprivation index for use in a specific population or to assess associations with specific health conditions. This was determined to be beyond the scope of this analysis, which is examining more general health applications.

3.1.1 Area Deprivation Index

The ADI was commonly used as a measure of neighborhood-level deprivation in the reviewed papers. This index was initially developed by the Health Resources and Services Administration but was put into broader use following the work of Singh (2003) and the later refinement by Kind et al. (2014). This deprivation index was built upon 17 socioeconomic indicators drawn from the 1990 U.S. Census and linked to mortality data to identify trends over time (Singh, 2003). These factors relate to education, unemployment, type of employment, home ownership, housing expenses, crowding within a home, ownership of a motor vehicle, home without a telephone, and single-parent households.

Table 4 Census Block Group Characteristics Comprising the Area Deprivation Index (as defined in Singh, 2003)

- Percent of population aged 25 years or older with less than 9 years of education
- Percent of population aged 25 years or older with less than a high school diploma
- Percent of employed persons aged 16 years or older in white-collar occupations
- Median family income
- Income disparity
- Median home value
- Median gross rent
- Median monthly mortgage
- Percent owner-occupied housing units (home ownership rate)
- Unemployment rate
- Percent of families below the poverty level
- Percent of population below 150% of the poverty threshold
- Percent of single-parent households with children < 18 years of age
- Percent of households without a motor vehicle
- Percent of households without a telephone
- Percent of occupied housing units without complete plumbing
- Percent of households with more than one person per room (crowding)

Kind et al. (2014) updated the ADI to 2000 U.S. Census data and validated the scale in the setting of rehospitalization rates among Medicare patients. The ADI uses census block group as the geographic unit of measure to approximate "neighborhood" and provides rankings of deprivation at the state and national levels. Of the studies included in this review, Chamberlain et al. (2020), Durfey et al. (2019), Hu et al. (2018), Knighton et al. (2016), and Maroko et al. (2016) all used the ADI as the basis for their assessments of neighborhood deprivation. Carlson et al. (2020) conducted a study to compare the ADI with the Neighborhood Stress Score (NSS), which was developed by MassHealth to incorporate social determinants of health into Medicaid and Children's Health Insurance Plan payment formulas within Massachusetts. In contrast to the ADI's 17 variables, the NSS incorporates 7 variables focusing on income, unemployment, receipt of public assistance, lack of motor vehicle, lack of high school diploma, and single-parent households (Ash et al., 2017).

3.1.2 Alternate Neighborhood Deprivation Indices

Five of the studies reviewed employed deprivation indices other than the ADI. These will be briefly discussed here.

Bhavsar et al. (2018) used data from the American Community Survey and calculated a neighborhood socioeconomic status index based upon the Agency for Healthcare Research and Quality's socioeconomic status index. This index factors in household crowding, median home value, unemployment, poverty status, median household income, percentage of adults with a bachelor's degree or higher, and percentage with less than a high school diploma.

Butler et al. (2013) used Primary Care Service Areas, which are groups of Zip Code Tabulation Areas as defined in the Dartmouth Atlas of Health Care (https://www.dartmouthatlas.org), combined with data from the American Community Survey to form the basis of the social deprivation index used in their assessment of geographical influence on health access and outcomes.

Kolak et al. (2020) combined publicly available data on 71,901 census tracts within the continental United States and 789 in Chicago with social determinants compiled through a review of frameworks and guidelines provided by multiple organizations. The researchers chose to use census tracts as the geographic segment for their analysis to look for neighborhood variability at a smaller scale than used for other indices. Their index included 15 variables stratified into three "environments": social, economic, and physical.

Liaw et al. (2013) conducted their analysis by identifying cold spots, defined as "census tracts with worse income, education, and composite deprivation" (p. 342), within Fairfax, Loudoun, Prince William, Fauquier, and Arlington counties in northern Virginia. These were identified using measures from the American Community Survey, the Social Deprivation Index

(Butler et al., 2013), and life expectancy data from the Virginia Department of Health. Patient data obtained via EHRs was geocoded to the census tract level and then the tracts matched with their community characteristics.

Xiao et al. (2016) employed a neighborhood deprivation index originally developed by Messer et al. (2006) to study the correlation of self-reported health among individuals aged 50–71 in California, Florida, Louisiana, New Jersey, North Carolina, and Pennsylvania, as well as in the metropolitan areas of Atlanta, Georgia, and Detroit, Michigan. The Messer et al. index was constructed by analyzing birth outcome data obtained from eight study areas and linking it at the census tract level to domains of poverty, housing, occupation, employment, education, residential stability, and racial composition to examine variability in perinatal health outcomes. Xiao and colleagues analyzed 10 census tract–level variables related to socioeconomic deprivation and their relationship to the self-reported health survey data.

3.1.3 Commonalities Among Deprivation Indices Used

Despite the variability in the specific deprivation indices used in the reviewed studies, some commonalities exist in the overall construction and use of these measures. These deprivation indices are developed to approximate the level of material and social deprivation within a given geographic area. The studies included in this review describe “neighborhood” at the census tract or block group level. These areas are smaller in scale than areas covered within a zip code. Zip codes also do not have set or defined boundaries and can cover populations of 100,000 or more. In contrast, census tracts and block groups have clearly defined geographic borders. Census tracts range from 1,200 to 8,000 in population and are composed of multiple smaller block groups, which consist of 600 to 3,000 individuals (U.S. Census Bureau, n.d.). These smaller, more defined areas are more homogenous with regard to availability of local amenities and resources, as well as income level and other socioeconomic indicators. As residential addresses are identified for inclusion in the studies, they are geocoded to their corresponding census tract or block group.

The deprivation indices employed in these studies use socioeconomic indicators derived from publicly available databases. The American Community Survey is an ongoing survey collecting and compiling datasets related to social, economic, housing, and demographics that are broken down into parcels as small as the census block group level. Combined, these indicators provide a relative measure of the living conditions within a geographic area.

3.2 Variables of Interest

In the identified studies, deprivation indices were used to assess correlations with a variety of health- and healthcare-related variables. Several studies examined associations between area deprivation and healthcare access, utilization, and outcomes. Bhavsar et al. (2018) employed a measure of neighborhood socioeconomic status (nSES) to assess correlations between deprivation status and use of healthcare services and hospitalizations related to accidents, asthma, influenza, myocardial infarction, and stroke. Butler et al. (2013) geocoded primary-care provider addresses gleaned from the American Medical Association Masterfile and the Center for Medicare and Medicaid Services to determine the number of providers available per 100,000 population. This formed the basis for scoring access to healthcare. The researchers also drew from the Dartmouth Atlas to capture the number of avoidable hospitalizations, defined as hospitalizations for conditions that could be properly managed in the primary care setting to reduce the likelihood of hospitalization. Maroko et al. (2016) also used hospitalization data as the variable of interest in their study using a locally adjusted ADI. Similarly, Carlson et al. (2020) looked at emergency department visits as the variable of interest in comparing the predictive value of two different deprivation indices.

Readmission rates were the focus of studies conducted by Kind et al. (2014) and Hu et al. (2018). Both studies looked at correlations between neighborhood-level deprivation scores and 30-day rehospitalizations.

Chronic disease also appeared as a variable of interest in several studies. Durfey et al. (2019) examined the relationship between neighborhood disadvantage and control of diabetes, blood pressure, and cholesterol level. Chamberlain et al. (2020) examined the association between deprivation score and multiple chronic conditions. Liaw et al. (2018) looked at associations between living in deprived communities and obesity rates, uncontrolled diabetes, frequency of pneumonia vaccination, rates of cancer screening, and aspirin use (as an indicator of cardiovascular disease).

In the Kolak et al. (2020) study, premature mortality served as the variable of interest. This was defined as death occurring before the age of 75, and the association between social determinants and premature death was assessed within Chicago, Illinois.

Xiao and colleagues (2017) assessed data on self-reported health drawn from the National Institutes of Health (NIH)/AARP Health and Diet Study to examine any correlations with neighborhood-level socioeconomic deprivation.

3.3 Geographic Locations and Defined Neighborhood Parameters

The studies reviewed in this assessment cover a range of geographic areas within the United States. The differences in the makeup of the geographic area studied can impact the interpretation of the results. For example, results can be affected based on study of urban versus rural areas, study of areas of higher socioeconomic status versus middle or lower, and factors such as population age, race, and education level. As such, the results may not be generalizable to other locations. The scope of what is defined as the “neighborhood” in these studies—the areal measure use to define the boundaries—also can influence the interpretation and comparison of the results.

As shown in Table 4, several of the reviewed studies included populations from across the United States. Others identified populations at the state, county, or city level. Within these geographic locations, the neighborhood-level analysis may be performed at the zip code level, census tract level, or census block group level. As previously discussed, census tracts typically contain populations of 1,200–8,000, whereas block groups are smaller, consisting of 600–3,000 individuals. The way in which neighborhood boundaries are defined in these studies is important to consider when examining the associations of the deprivation indices with the variables of interest.

Table 5 Summary of Geographic Areas Studied and Defined Neighborhood Level

Study	Geographic Location Examined	Neighborhood Parameter
Bhavsar et al. (2018)	Durham County, NC	Census tract level
Butler et al. (2013)	United States	Primary care service area (combinations of Zip Code Tabulation Areas, constructed from census blocks)
Carlson et al. (2020)	Boston, Massachusetts	Census block group level
Chamberlain et al. (2020)	7 counties in Minnesota	Census block group level
Durfey et al. (2019)	United States	Zip+4 linked to census block group
Hu et al. (2018)	Detroit, Michigan	Census block group level
Kind et al. (2014)	United States and District of Columbia	Census block group level (also assessed rurality of zip codes for patients)
Knighton et al. (2016)	Salt Lake City, Utah	Census block group level
Kolak et al. (2020)	Continental United States	Census tract level
Liaw et al. (2018)	5 counties in northern Virginia	Census tract level
Maroko et al. (2016)	8 counties in New York	Compared multiple geographic levels (10 km, 20 km, 30 km, and the entire Hudson Valley region)
Xiao et al. (2017)	States of California, Florida, Louisiana, New Jersey, North Carolina, and Pennsylvania; cities of Atlanta, Georgia, and Detroit, Michigan	Census tract level

3.4 Study Findings

As discussed in the preceding sections, the studies included in this review have explored the effect of neighborhood-level deprivation on a range of outcomes. Social determinants clearly have an impact on individual health, but these studies demonstrated the predictive ability of geographic indices of deprivation, albeit with variation associated with the outcomes measured.

This section will examine the conclusions reached in these studies based on the data analyses performed around the research on deprivation indices. The first seven studies discussed herein used the ADI as a measure of deprivation, and the last five employed other indices.

3.4.1 Chamberlain et al. (2020)

In a study exploring the link between living in a deprived neighborhood and experiencing multiple morbidities, the authors reviewed medical records from participants in the Rochester Epidemiology Project who resided in a seven-county region of southern Minnesota. Participants' records were examined for multiple chronic conditions based on ICD 9/10 diagnostic codes. ADI scores at the census tract level were assigned to each participant based on geocoded addresses. The ADI comprises 17 variables as discussed previously. In this analysis, all but two of the variables in the ADI had an association with multiple morbidities (households lacking a telephone and households with more than one person per room). Individuals in the highest quintile of ADI had a 50% higher risk of multimorbidity than those in the lowest ADI quintile and also had a 60% higher risk of severe multiple morbidities. The authors found that adjusting for education level produced even stronger associations. The effect was more pronounced in individuals younger than age 70. The authors concluded that the neighborhood can encompass a range of factors that impact health, such as safety, social bonds, access to food and healthcare, and education. Adding an ADI score to patient information can facilitate identification of high-risk individuals and referral to community-based services for care management.

3.4.2 Carlson et al. (2020)

Carlson and colleagues compared the Neighborhood Stress Score (NSS), a deprivation scale developed by MassHealth (the manager of Medicare and the Children's Health Insurance Program in Massachusetts), and ADI as predictors of acute care utilization. These two scales employ different U.S. Census indicators: the ADI uses 17 indicators, whereas the NSS uses 7 (distance to visited hospital, distance to closest other hospital, median age, percent female, number of emergency department visits per year per 100 persons, number of hospitalizations per year per 100 persons, and number of emergency department utilizers per year per 100 persons). These scales were applied to patients at two academic medical centers in Boston, Massachusetts, to assess impact of neighborhood-level deprivation on utilization of emergency department services and hospitalizations for ambulatory care–sensitive conditions (defined as healthcare conditions that could be prevented through use of primary care services). Patient addresses were geocoded to census block group level. The Neighborhood Atlas (described earlier in this paper) was used to match census block groups with ADI score. For the NSS, values for the census block groups were calculated based on American Community Survey data for the seven variables used.

In comparing results, both indices demonstrated increases in preventable admissions and emergency department visits with increasing level of deprivation. This supports the association between SDOH and preventable hospital visits. The data analysis revealed the NSS as a stronger predictor of these healthcare utilizations. This could indicate that the particular deprivation indicators used by the NSS may be more closely tied to preventable healthcare encounters than the 17 indicators used in the ADI.

Numerous studies have assessed the effectiveness of the ADI in population health management. The NSS can be useful for targeting care intended to prevent hospitalizations and emergency department visits as well as for developing community-based programs and interventions to address SDOH. One caveat is that this study population was drawn from patients seeking care at facilities in a large urban area, and thus the results may not be broadly applicable to other geographic areas.

3.4.3 Durfey et al. (2019)

In an analysis of patient data obtained from the Centers for Medicare and Medicaid Services, Durfey et al. (2019) sought to examine whether a relationship exists between neighborhood-level deprivation and control of diabetes, blood pressure, and cholesterol. This study employed the ADI as the measure of neighborhood deprivation. For this secondary analysis, the authors linked residential addresses for Medicare Advantage enrollees in the data set to census block groups through their residential 9-digit zip code. Block groups were then matched to the ADI to establish a measure of deprivation for each location. The individuals in this large sample were drawn from across the United States. Information on race, gender, disability, and dual eligibility also were obtained for the sample.

Statistical analysis revealed that neighborhoods falling into the highest levels of deprivation included higher proportions of individuals with poorly controlled blood pressure, diabetes, and cholesterol. The most disadvantaged neighborhoods had higher proportions of Black individuals than did the least disadvantaged. An association also was found between high level of disadvantage and living in the most rural areas as well as higher proportion of disabled individuals. The authors concluded that ADI can effectively predict control of diabetes, hypertension, and hyperlipidemia and that the relationship did not differ by race/ethnicity. They determined that the ADI could be a useful proxy measure for SDOH to target interventions at the geographic level.

3.4.4 Hu et al. (2018)

Hu and colleagues conducted an analysis of 30-day hospital readmissions among Medicare fee-for-service patients discharged from Henry Ford Hospital in Detroit, Michigan. Patient data were drawn from the hospital's repository, and patient addresses were geocoded to the census block group level to associate each with a corresponding ADI score. These were then linked to the hospital's readmission data for the cohort. The study area has one of the highest concentrations of deprived neighborhoods in the United States, so the ADI distribution was compared to that of the United States as a whole. This cohort contained more patients living in the highest areas of deprivation than is seen in the nation overall.

Regression analysis showed that patients living in high-deprivation neighborhoods had significantly greater likelihoods of experiencing readmissions. Individuals living in the 5% most deprived areas had a 70% greater risk of readmission than individuals in lower-ADI neighborhoods. Among individuals residing in the areas of less deprivation, there was little difference in readmission rates, suggesting that a threshold for a minimum level of social support services exists within a neighborhood. Once this level is achieved, patients are not likely to experience readmissions. This study supports the assertion that use of quality measures in the healthcare setting, such as those related to readmissions, could be enhanced by considering neighborhood-level factors Access to a baseline level of services and resources in a neighborhood can influence patient outcomes. As the authors note, "Being poor in a high-disadvantage neighborhood or community is not the same experience as being poor in a low-disadvantage neighborhood or community" (p. 500).

Given that this study utilized data from a single hospital in a highly disadvantaged region, the results may not be generalizable to areas with different socioeconomic characteristics. The authors note, however, that by drawing from a single facility, the level of care and scope of services provided are consistent, thereby reducing the potential for confounders. Information on the reasons for readmissions was not available, and the authors note that this could be important to explore in future research.

3.4.5 Kind et al. (2014)

In this study, Kind et al. (2014) sought to assess the relationship between ADI and 30-day readmissions among a large random national sample of Medicare patients who had initially been hospitalized for congestive heart failure, pneumonia, or myocardial infarction. Rehospitalizations for these conditions lead to payment penalties for hospitals providing care to patients covered by Medicare, so reducing readmissions could be beneficial for both patients and providers.

As in the Hu et al. (2018) study, the authors used patients' 9-digit zip code to link residences to census block groups. An ADI was calculated for each block group to determine the deprivation score. The authors conducted multivariate analysis to determine whether relationships existed between ADI and readmissions. The top 15% most disadvantaged block group neighborhoods had readmission rates of 22%–27%, compared to an average of 25% for the other 85% of neighborhoods. In the most disadvantaged neighborhoods, the rate increased as deprivation score worsened. Patients in the most deprived areas experienced readmission rates similar to rates seen in patients with chronic pulmonary disease. In assessing patients with similar characteristics treated at the same hospital but having different neighborhood deprivation levels, deprivation level was show to impact rate of rehospitalization. Rural areas also were associated with higher levels of deprivation, with 32% of patients in small towns and rural areas residing in the 15% most deprived neighborhoods, compared to 20% of patients in urban and suburban areas. The authors propose that if neighborhood deprivation level were accessible to providers at the point of care, more individualized post-discharge plans could be provided to patients in areas of high deprivation. Given that social needs screening is not widely performed and socioeconomic status is not available in patient records, the addition of ADI within hospital settings could serve as a useful proxy for identifying patients who may be experiencing disadvantage that could be contributing to poor health outcomes. However, the risk exists for introducing ecological fallacy by attributing population-level traits to individuals and overlooking their unique experiences. More research into integration of ADI into patient healthcare records is needed.

3.4.6 Knighton et al. (2016)

Knighton et al. (2016) sought to calculate an ADI for the state of Utah in an attempt to provide a geographically based index to serve as a proxy for patient-obtained data on disadvantage that could be used in the Intermountain Healthcare system. Manual collection of information on SDOH has been viewed as inefficient, and many electronic patient data management systems lack structured methods for capturing this information. Thus, the authors adapted the ADI developed by Singh (2003) for specific use in Utah to test the effectiveness of incorporating ADI as a measure of social determinants to enhance clinical practice and research endeavors.

The Utah ADI was calculated for each census block group in the state according to the method outlined by Singh in the initial development of the ADI. The authors obtained data on patients treated at Intermountain Healthcare facilities and matched patient addresses to the corresponding census block group. Block groups then were linked to the corresponding ADI, so each address was associated with an ADI score.

Limitations of this study include the relative homogeneity of the Utah population. The population is less racially diverse than the United States as a whole and has a higher mean household income than the national average. There was, however, a high level of disparity between the highest and lowest block group ADI scores, which indicates extremes of both wealth and poverty in the state. The Utah ADI has been applied to several projects in the health system for which brief case studies were presented. One initiative is aimed at identifying patients at high risk for multiple chronic conditions to facilitate connection to community-based services. Another involves the development of a community health needs assessment using the block group ADI scores to identify the most deprived areas in the region. This information has been shared with stakeholders to inform discussions on community needs. The Utah ADI also has been used to evaluate the effect of neighborhood deprivation on adherence to treatment for hypertension. The methods used by the authors could be adapted by other states to develop an ADI that is more specific to their populations. Limitations to the ADI noted by the authors include the heavy reliance on home values in the calculation of ADI, but some census block groups have limited numbers of residences from which to draw this information, requiring imputation for missing values. Aggregating population-level characteristics to individuals comes with some inherent bias.

3.4.7 Maroko et al. (2016)

As with Knighton et al. (2016), Maroko et al. (2016) explored the utility of an ADI to assess deprivation within a designated region, in this case the Hudson Valley area of New York State. Using the University of Wisconsin’s ADI developed for the United States, the authors calibrated the ADI to the eight-county Hudson Valley region. The authors collected data on hospitalizations for individuals from the New York State Department of Health and examined correlations between hospitalization rates and ADI. The top 15% of ADIs were identified as the threshold for deprivation (as established by Kind et al., 2014), and ADI was calculated at three geographic radiuses: 10 km, 20 km, and 30 km. The smallest geographic area showed the strongest associations between ADI and hospitalization rates, demonstrating that adjusting ADI at smaller geographic levels is a more effective method for estimating deprivation than by applying scales to a local area that have been developed using national estimates. The ADI does appear to have utility to inform clinical care and facilitate connection of patients to community resources and address SDOH. The authors posit that using smaller aggregate units such as census tracts could increase the sensitivity of an ADI.

3.4.8 Bhavsar et al. (2018)

As a measure of risk for using emergency and inpatient/outpatient health services, the nSES scale used in a large cohort study by Bhavsar et al. (2018) showed correlations between lower nSES score (indicating greater deprivation) and shorter time to healthcare events such as emergency department visits and hospitalizations. Of particular note is that, although nSES was predictive for health outcomes in the study population, adding these data to the EHR did not improve the predictive ability of the EHR for patients with regard to emergency department visits and healthcare encounters associated with accidents, asthma, influenza, myocardial infarction, and stroke. EHRs typically lack information about patients' socioeconomic status and social environments, but the demographic information, such as age, sex, race, and type of insurance, as well as prior healthcare utilization information contained in the EHR appear to be predictive of clinical outcomes. Although the study population was large, it was drawn from a single geographic region, and the EHR data were extracted from a single, large academic health system (Duke

University Health System), and this could affect the type and quality of care to which this population has access and could bias results. Durham County, North Carolina, does, however, contain both rural and urban communities and residents representing a broad range of socioeconomic status. As patient outcomes are increasingly tied to reimbursement for healthcare providers, utilization of readily available data to manage population health holds great appeal, but this study appears to demonstrate that existing patient data could be harnessed to perform predictive analyses.

3.4.9 Butler et al. (2013)

Butler and colleagues developed a social deprivation index to measure healthcare access and health outcomes across primary care service areas in the United States, which approximate the use of primary care by Medicare beneficiaries. This provides an overall picture of healthcare usage for individuals who have consistent access to care. Access to care was measured by mapping the addresses of primary care physicians, nurse practitioners, and physician assistants and calculating the availability of providers within the primary care service areas. The deprivation index was used to conduct an analysis of mortality, infant mortality, low birth weight rates, and diabetes prevalence within geographic areas. The social deprivation index demonstrated a positive association with these outcomes and held consistent when controlling for variables related to healthcare access. The researchers also compared the predictive ability of this index with level of poverty, which is a common metric for identifying underserved geographic areas in the United States. The social deprivation index in this study demonstrated an improvement in predicting resource need over the use of poverty alone, which supports the argument for considering additional measures of deprivation when allocating resources to better assess where need is greatest within a geographic area.

One limitation is whether primary care service areas are reflective of other patient populations, particularly younger individuals and individuals with less reliable health insurance. Some of the outcomes were estimates based on the availability of data at the county level (e.g., lack of insurance, avoidable hospitalizations). This may not accurately represent variability within the geographic area and across the service areas.

3.4.10 Kolak et al. (2020)

The authors of this study sought to explore the complexities underlying social and economic disparities in the United States through creation of an index to quantify social determinants that can be used to inform policy. Using 15 variables to represent SDOH, the researchers endeavored to address the geographic heterogeneity that may be overlooked by existing indices such as the ADI by analyzing SDOH at the regional level across the United States. Using publicly available census tract–level data, the authors examined relationships between geographic area and sociodemographic characteristics. They identified four core components to represent deprivation: socioeconomic advantage, limited mobility, urban core opportunity, and mixed immigrant cohesion and accessibility. As expected, socioeconomic disadvantage accounted for 40% of the total variance across census tracts. However, the social and neighborhood characteristics combined accounted for approximately the same level of variance. This speaks to the complex interplay of factors affecting deprivation and that geographic factors should be considered when assessing a population for SDOH and when implementing health-related policies.

Economic deprivation alone may underestimate the impact of the social environment on health, as also concluded by Butler et al. (2013).

3.4.11 Liaw et al. (2018)

Liaw and colleagues sought to explore the incorporation of geographic deprivation data into clinical care by tying community deprivation scores to EHR data for patients at 12 private medical practices within a 45-mile radius covering several counties in northern Virginia. The authors geocoded the addresses for more than 150,000 patients seen at these practices and linked their corresponding census tracts to the level of deprivation as defined in the social deprivation index. This includes measures related to education, household crowding, type of housing, presence of single-parent household, access to transportation, employment, and poverty. Census tracts with the worst scores on these measures were designated as "cold spots." Clinical outcomes measured included obesity, uncontrolled diabetes, pneumonia vaccination, common cancer screenings, and use of aspirin for cardiovascular disease. Data analysis found that living in cold spots influenced all measures other than aspirin use. Approximately 13% of the patients included in this study were found to reside in cold spots despite the fact that the counties of residence are some of the more affluent in the country. This speaks to the utility of multidimensional measures of deprivation rather than just use of census tract–based median income. One interesting note is that patients residing in areas of higher educational deprivation were more likely to receive cervical cancer screening and pneumonia vaccinations. These areas may be conducting additional outreach that encourages these preventative measures.

Given that this study does involve a region of overall high affluence, the results may not be generalizable to other areas or practices. The provider-level factors also are unknown in this study, such as the quality of patient communication.

3.4.12 Xiao et al. (2017)

In a study comparing self-rated health and neighborhood-level deprivation, Xiao et al (2017) conducted a large cohort study using data obtained from a subset of participants in the NIH-AARP Diet and Health survey over a 10-year period. Self-rated health is shown to be a strong predictor of quality of life and mortality, especially in older adults, and Healthy People 2020 tracks this measure in the U.S. population. Nearly 250,000 participants were recruited from six states and two metropolitan areas and asked to rate their overall health as very good, good, fair, or poor. Additional demographic and lifestyle information was obtained from the survey. Participants' addresses were geocoded and linked to census tract. The authors developed a social deprivation scale derived from 19 census tract–level variables that represent neighborhood characteristics (e.g., housing characteristics and stability, poverty, employment, racial distribution, education level) and matched the geocoded addresses to the corresponding deprivation level.

The authors found that participants living in neighborhoods with higher deprivation scores were more likely to self-rate their health as fair or poor over the course of the study. This association remained even after adjusting for factors such as socioeconomic status and health conditions and behaviors, indicating that external factors are impacting perceived health. The participants in this study were more educated and had higher incomes than the U.S. average, and the cohort was predominantly White. The authors noted that even in this relatively homogenous sample, the most deprived group was twice as likely to report fair or poor health, and the disparity within the U.S. population as a whole could be greater.

4.0 Discussion

This literature review was conducted to identify current research in the development and use of neighborhood-level deprivation indices in the United States to address SDOH and healthcare utilization. It has been well-established that neighborhood-level factors affect the health of individuals and the utilization of healthcare services. Screening patients for unmet social needs in the clinical setting, although advocated by healthcare associations and the Centers for Medicare and Medicaid Services, is not widely performed; as such, availability of information on SDOH obtained directly from patients is limited. The study of methods to quantify the level of deprivation in an area as a predictor of health outcomes has gained momentum over the past 15 years as researchers look to estimate deprivation at the community level in the absence of individual-level SDOH data. This review contains a sampling of 12 of these studies with a focus on general health and chronic conditions in adults as well as the utilization of emergency and inpatient healthcare services.

The majority of the studies in this review utilized iterations of the ADI, as first developed by Singh (2003) and made widely available through the University of Wisconsin School of Medicine and Public Health's Neighborhood Atlas project, as the basis for measuring area-level deprivation. Several others set out to construct and test indices using alternate indicators of deprivation. Across all studies, neighborhood-level deprivation demonstrated predictive ability for the variables of interest. Some variations exist, though, in the nature of the relationships between areal deprivation and health. The following sections will explore the potential uses of deprivation indices in population risk assessment and clinical care, as well as the limitations of their use, as identified through these studies.

4.1 Utility of Geographic Deprivation Indices

As discussed throughout this review, composite measures of deprivation at the neighborhood level demonstrate utility in predicting healthcare utilization and chronic disease management. The highest levels of deprivation were associated with increased risk of hospital readmissions, utilization of acute-care services for potentially preventable health conditions, presence of multiple health conditions, poor control of chronic conditions, mortality, and poor self-reported health.

The ADI has formed the foundation of research into neighborhood-level deprivation in the United States and has been validated as a predictor of rehospitalizations for patients experiencing chronic health conditions. It is constructed using 17 census block group–level variables to broadly represent level of deprivation within a small geographic area, the census block group. Use of measures such as the ADI that aggregate neighborhood-level socioeconomic characteristics, as represented by factors such as education level, income, home value, rent/mortgage payment, vehicle ownership, and home ownership rate, capture a wide range of experiences of individuals in a community that may have predictive value with regard to the health of its people. The ADI has particular utility in the clinical setting when incorporated into EHR systems to address SDOH. By assigning an ADI score to patients based on their residential address, the EHR can flag patients living in areas of high deprivation to alert clinicians that these individuals may benefit from social needs screening during a clinical encounter. This ultimately can assist with addressing nonmedical variables that may be contributing to poor health, such as food and housing insecurity, lack of transportation, interpersonal violence, and lack of ability to pay for healthcare services or medications.

As an alternative index to the ADI, the NSS developed by MassHealth and used by Carlson et al. (2020) takes into account several healthcare access variables in calculating its neighborhood deprivation score. This scale considers proximity to hospitals and number of emergency department visits and hospitalizations per year per 100 persons in the population, as well as age and gender breakdown. Incorporating these indicators provides a more targeted assessment for use in predicting acute care utilization, as done in this study. This demonstrates the benefit of selecting targeted factors to measure deprivation based on the outcome of interest in the study. An index such as the NSS could be valuable for incorporation into hospital quality improvement initiatives, affecting reimbursement and incentives for reducing utilization of high-cost care.

In the Butler et al. (2013) study, the social deprivation index was developed using variables contained in the British Townsend index (overcrowded living spaces, lack of vehicle for the household, and percent of unemployed adults) and adding variables related to percent of population younger than age five and percentage female of typical reproductive age. In comparing this index to a purely socioeconomic measure of poverty in the United States, as is used in identifying medically underserved areas, the multidimensional index is more predictive of healthcare access and health outcomes. Applying a composite geographic measure of deprivation could improve population risk assessment and better inform policy and decisions regarding more equitable distribution of resources to address disparities.

The availability of reproducible deprivation indices through the literature allows health departments, policy makers, and researchers to more readily assess a local geographic area for deprivation when seeking to develop quality improvement initiatives and community-based interventions. For example, Knighton et al. (2016) used the ADI established at the University of Wisconsin School of Medicine and Public Health to construct a localized version for the state of

Utah and concluded that the adapted ADI could have utility in addressing SDOH within a regional health system.

Smaller geographic areas seem to provide a more reliable measure of deprivation, as also noted by Knighton et al. (2016). Use of zip code or census tract was less effective for identifying the effect of the measures of deprivation included in the ADI than was the smaller block group level. Maroko et al.'s (2016) study supports this conclusion. Testing a locally adjusted version of the ADI in geographic areas of differing sizes demonstrated stronger associations between level of deprivation and health outcomes at smaller geographic regions. Even within relatively small regions such as a census tract or zip code, variations can exist in the deprivation experienced by residents, and this deprivation can result in uneven access to healthcare and variability in health outcomes. This may be of particular relevance to health systems when considering the incorporation of deprivation scores into EHRs to target patients for interventions. Ensuring that the deprivation scales are appropriately calibrated to the smallest geographic area possible can provide a more realistic approximation of individuals' risk of being impacted by SDOH because of where they live.

The studies examined in this review looked at area deprivation scales from the perspectives of application within the clinical setting as proxies for social needs screening, within healthcare systems as part of quality improvement initiatives, and in policy and program development to address healthcare disparities. Studies using the ADI have shown effectiveness in predicting which patients may be experiencing poorly controlled chronic health conditions and multiple morbidities as well as greater risk of readmissions. Other indices developed and used in the reviewed literature have examined the predictive value of other deprivation variables for estimating rates of utilization of emergency services and inpatient/outpatient healthcare, health outcome measures, mortality, management of chronic conditions, and self-reported health.

4.2 Limitations of Geographic Deprivation Indices

Despite the potential for the use of neighborhood-level deprivation scales for risk management and quality improvement in the clinical setting as well as in forming healthcare policy and development of community-based interventions, this literature review has elucidated a number of limitations of their use.

Despite the noted validity of composite indices in estimating potential deprivation in a small geographic area, the use of aggregate measures of deprivation to represent the levels of need for individuals is subject to some criticism. As noted by Butler et al. (2013), there is value in using widely available data, such as the socioeconomic data collected via the U.S. Census and American Community Survey, to represent regional sociodemographic characteristics, but this value comes at the expense of specificity. Diez Roux and Mair (2010) echo this, noting that these composite indices do not specifically identify the most impactful deprivation factors within a neighborhood, so it may be difficult to determine causal links between particular elements and health outcomes. Comparing the predictive ability of different indices is challenging, as different deprivation variables are used in the construction of indices. Because these indices are compilations of numerous deprivation factors, it is not clear what specific neighborhood-level factor or factors are actually contributing to the outcomes being measured and to what degree. As such, the use of neighborhood deprivation scales to identify what specific interventions may be most beneficial to the health of a community would require additional research.

As Kind et al. (2014) noted, the issue of ecological fallacy, in which an area's traits are attributed to individuals residing in the area, is also a limitation of these deprivation indices. Extrapolating from deprivation scores and making direct assumptions about the lives and behaviors of individual patients can lead to missed opportunities to aid those who reside in areas with lower deprivation scores but may still be experiencing unmet social needs. This speaks to the value of conducting social needs screening broadly in the clinical setting to ensure that actual patient experiences are considered in treatment planning, not solely those at the neighborhood level.

Given the nature of U.S. Census–based data, which is collected at a point in time every 10 years, studies using these data sets can miss important changes that occur in neighborhoods over time, leading to inaccuracies in calculated deprivation scores. Using data from the American Community Survey helps to ensure that changes over time are considered, as these data are collected on a rolling schedule between national census periods. However, the American Community Survey is not administered to the entire U.S. population, so sampling error could be a concern. Census data also may not include complete data on more marginalized populations, and these individuals are at greater risk for experiencing problems related to healthcare access and the impact of SDOH.

Many of the factors included in the deprivation scales described in these studies are representative of socioeconomic status. Other factors at the neighborhood level, however, are missing from these composite indices. Ready access in the neighborhood to fresh groceries, areas for exercise and socialization, and other amenities can also impact health and well-being and but are not intrinsically linked to income or financial resources. Other factors such as exposure to violence, within the neighborhood or household, and substance use can impact health but are not included in these scales. Although some indices incorporate neighborhood-level data on education, health literacy is not considered in these scales. Health literacy has been shown to be a stronger predictor of health than factors such as age, income, education level, and race and is important to assess in all patients (American Medical Association, 1999). Finally, much of the research performed with deprivation indices involves analysis of data from secondary sources. Although use of large administrative data sets has clear benefits for research, additional studies using primary data could be useful in assessing the accuracy of these measures of deprivation.

In addition to the overall limitations of use of deprivation indices noted here, the studies examined for this review have several additional limitations. Most of the studies using deprivation scales other than the ADI have involved specific geographic regions, and these regions may have population characteristics that differ from the overall U.S. population, thereby reducing the generalizability of any associations between the scales and the outcomes of interest. A number of the geographic areas included in these studies tended to be less socioeconomically and racially diverse, such as Northern Virginia (Liaw et al., 2018), Salt Lake City (Knighton et al., 2016), the Hudson Valley region in New York (Maroko et al., 2016), Boston (Carlson et al., 2020), and Minnesota (Chamberlain et al., 2020). Rural areas were not widely represented in the studies. Xiao et al. (2017) used data that included individuals from several southern states as well as the Detroit area; however, the group overall was affluent, well educated, and primarily White. Kind et al. (2014) used data from the United States plus the District of Columbia, but Whites were still overrepresented in the sample (87%).

4.3 Areas for Future Research

Based on the results and limitations found in this review of literature on the development and use of geographic deprivation indices in the United States, some areas for additional research have been revealed. First, more longitudinal studies are needed to look at the effects of neighborhood-level deprivation over time. This will be beneficial to inform policy and public health interventions. As new deprivation scales are devised, particularly those incorporating fewer but more targeted deprivation variables, research comparing these scales to the existing ADI will be useful in identifying whether specific variables used in compiling deprivation indices have stronger associations with particular healthcare utilization or conditions. Research focusing on measurement of neighborhood deprivation in rural areas and areas with higher concentrations of minority populations is needed to increase understanding of the connections between geography and health in groups that have historically experienced poorer healthcare access and health outcomes. Finally, research that directly compares the effectiveness of social needs screening in the clinical setting with use of proxy measures for deprivation is needed to evaluate whether incorporation of deprivation scores into EHRs could substitute for broader social needs screening, as some of these studies suggest.

5.0 Conclusions

Unmet social needs have been shown to increase healthcare utilization and contribute to poor health outcomes for patients. As payors transition from fee-for-service reimbursement structures that reward volume of patients seen and procedures performed to models focusing on the value of the care provided, the interest in addressing SDOH will continue to increase. The lack of SDOH data in EHRs and the challenges associated with implementing large-scale social needs screening speak to the growing interest in identifying proxy measures for deprivation that can adjust for factors that may be adversely affecting patient health and care utilization. The studies reviewed in this paper take varying approaches to explore the links between neighborhood-level deprivation and health and the utility of deprivation indices to supplement existing patient data included in EHRs. Deprivation indices have not been determined to provide a direct substitute for performing social needs assessments in the clinical setting. However, as an adjunct to hospital quality measures, deprivation indices show promise. The ability to better address multiple morbidities and poorly managed chronic conditions and reduce hospital readmissions will improve quality of care and reduce overall healthcare costs and high-acuity care utilization. Identification of areas experiencing high levels of deprivation could also inform the expansion of primary care clinics into areas where patients can benefit from greater access to preventive and chronic disease management services, such as rural and urban areas. As the Patient Protection and Affordable Care Act requires nonprofit hospitals to conduct community health needs assessments every three years, deprivation indices could help to inform the development of programs and strategies directed at improving community health.

Screening for unmet social needs during a healthcare encounter, as recommended by various national entities, is the most effective way to ensure that clinicians are informed about patients' unmet needs and can use this information in developing personalized care plans that include connection with community resources to assist with meeting unmet needs. The incorporation of neighborhood-level deprivation scores into EHR data can provide clinicians with a more complete picture of the multitude of factors that can be affecting patient health beyond just lifestyle and genetics and facilitate referral to services within a patient's community to address unmet social needs. This can be an important step toward reducing the disparities in care and outcomes that have persisted in the United States and ensure that all individuals, regardless of their socioeconomic situation and geographic location, are treated equitably within the existing U.S. healthcare system and provided with access to the supports and services that can help them to achieve optimal health and quality of life.

Neighborhood-level deprivation indices show promise to aid health systems in addressing SDOH and managing costs associated with preventable conditions and care utilization, to encourage clinicians to take steps to identify and address patients' unmet social needs, to inform healthcare policy, and to guide the development and implementation of targeted public health programs aimed at addressing health disparities at the neighborhood level. Further research is needed to identify whether particular health conditions are more strongly linked with deprivation and whether use of indices focusing on deprivation at the macro level can effectively serve as a proxy for social needs screening at the patient level.

Bibliography

American Medical Association. (1999). Health literacy: Report of the Council on Scientific Affairs. Ad Hoc Committee on Health Literacy for the Council on Scientific Affairs, American Medical Association. *JAMA, 281*(6), 552-557.

Amjad, S., MacDonald, I., Chambers, T., Osornio-Vargas, A., Chandra, S., Voaklander, D., & Ospina, M. B. (2019). Social determinants of health and adverse maternal and birth outcomes in adolescent pregnancies: A systematic review and meta-analysis. *Paediatric Perinatal Epidemiology, 33*(1), 88-99. https://doi.org/10.1111/ppe.12529

Arroyo-Johnson, C., & Mincey, K. D. (2016). Obesity epidemiology worldwide. *Gastroenterology Clinics of North America*, *45*(4), 571-579. https://doi.org/10.1016/j.gtc.2016.07.012

Artiga, S., Orgera, K., & Pham, O. (2020). *Disparities in health and health care: Five key questions and answers*. https://www.kff.org/disparities-policy/issue-brief/disparities-in-health-and-health-care-five-key-questions-and-answers/

Ash, A. S., Mick, E. O., Ellis, R. P., Kiefe, C. I., Allison, J. J., & Clark, M. A. (2017). Social determinants of health in managed care payment formulas. *JAMA Internal Medicine, 177*(10), 1424-1430. https://doi.org/10.1001/jamainternmed.2017.3317

Bhavsar, N. A., Gao, A., Phelan, M., Pagidipati, N. J., & Goldstein, B. A. (2018). Value of neighborhood socioeconomic status in predicting risk of outcomes in studies that use electronic health record data. *JAMA Network Open*, *1*(5), e182716. https://doi.org/10.1001/jamanetworkopen.2018.2716

Bui, T., George, L., Bowersox, M., & Hawk, M. (2020). *Hospital-based initiatives to address unmet social needs of high-risk patients.* Society of General Internal Medicine 2020 Virtual Meeting. https://sgim-ccast.echo360.org/meeting-detail-about.aspx/4

Butler, D. C., Petterson, S., Phillips, R. L., & Bazemore, A. W. (2013). Measures of social deprivation that predict health care access and need within a rational area of primary care service delivery. *Health Services Research*, *48*(2 Pt 1), 539-559. https://doi.org/10.1111/j.1475-6773.2012.01449.x

Byhoff, E., De Marchis, E. H., Hessler, D., Fichtenberg, C., Adler, N., Cohen, A. J., Doran, K. M., Ettinger de Cuba, S., Fleegler, E. W., Gavin, N., Huebschmann, A. G., Lindau, S. T., Tung, E. L., Raven, M., Jepson, S., Johnson, W., Olson, A. L., Sandel, M., Sheward, R. S., & Gottlieb, L. M. (2019). Part II: A qualitative study of social risk screening acceptability in patients and caregivers. *American Journal of Preventive Medicine, 57*(6 Suppl 1), S38-S46. https://doi.org/10.1016/j.amepre.2019.07.016

Carlson, L. C., Kim, J., Samuels-Kalow, M. E., Yun, B. J., Terry, D. F., Weilburg, J. B., & Lee, J. (2020). Comparing neighborhood-based indices of socioeconomic risk factors and potentially preventable emergency department utilization. *American Journal of Emergency Med*icine. https://doi.org/10.1016/j.ajem.2020.03.035

Chamberlain, A. M., Finney Rutten, L. J., Wilson, P. M., Fan, C., Boyd, C. M., Jacobson, D. J., Rocca, W. A., & St Sauver, J. L. (2020). Neighborhood socioeconomic disadvantage is associated with multimorbidity in a geographically-defined community. *BMC Public Health, 20*(1), 13. https://doi.org/10.1186/s12889-019-8123-0

Commission on Social Determinants of Health. (2008). *Closing the gap in a generation: Health equity through action on the social determinants of health. Final Report of the Commission on Social Determinants of Health*. Geneva, Switzerland: World Health Organization.

Coughlin, S. S. (2019). Social determinants of breast cancer risk, stage, and survival. *Breast Cancer Research and Treatment, 177*(3), 537-548. https://doi.org/10.1007/s10549-019-05340-7

De Marchis, E. H., Hessler, D., Fichtenberg, C., Adler, N., Byhoff, E., Cohen, A. J., Doran, K. M., Ettinger de Cuba, S., Fleegler, E. W., Lewis, C. C., Lindau, S. T., Tung, E. L., Huebschmann, A. G., Prather, A. A., Raven, M., Gavin, N., Jepson, S., Johnson, W., Ochoa, E., Jr., … Gottlieb, L. M. (2019). Part I: A quantitative study of social risk screening acceptability in patients and caregivers. *American Journal of Preventive Medicine, 57*(6 Suppl 1), S25-S37. https://doi.org/10.1016/j.amepre.2019.07.010

Diez Roux, A. V., & Mair, C. (2010). Neighborhoods and health. *Annals of the New York Academy of Science, 1186*, 125-145. https://doi.org/10.1111/j.1749-6632.2009.05333.x

Diez-Roux, A. V. (1998). On genes, individuals, society, and epidemiology. *American Journal of Epidemiology, 148*(11), 1027-1032. https://doi.org/10.1093/oxfordjournals.aje.a009578

Durfey, S. N. M., Kind, A. J. H., Buckingham, W. R., DuGoff, E. H., & Trivedi, A. N. (2019). Neighborhood disadvantage and chronic disease management. *Health Services Research, 54*(Suppl 1), 206-216. https://doi.org/10.1111/1475-6773.13092

Fraze, T. K., Brewster, A. L., Lewis, V. A., Beidler, L. B., Murray, G. F., & Colla, C. H. (2019). Prevalence of screening for food insecurity, housing instability, utility needs, transportation needs, and interpersonal violence by US physician practices and hospitals. *JAMA Network Open, 2*(9), e1911514. https://doi.org/10.1001/jamanetworkopen.2019.11514

Gold, R., & Gottlieb, L. (2019). National data on social risk screening underscore the need for implementation research. *JAMA Network Open, 2*(9), e1911513. https://doi.org/10.1001/jamanetworkopen.2019.11513

Havranek, E. P., Mujahid, M. S., Barr, D. A., Blair, I. V., Cohen, M. S., Cruz-Flores, S., Davey-Smith, G., Dennison-Himmelfarb, C. R., Lauer, M. S., Lockwood, D. W., Rosal, M., & Yancy, C. W. (2015). Social determinants of risk and outcomes for cardiovascular disease: A scientific statement from the American Heart Association. *Circulation, 132*(9), 873-898. https://doi.org/10.1161/cir.0000000000000228

Headspace. (2020). *Racial and gender health disparities: Listening with Dr. Wizdom Powell*. https://www.youtube.com/watch?v=t7Z96sbIqUM

Hu, J., Kind, A. J. H., & Nerenz, D. (2018). Area deprivation index predicts readmission risk at an urban teaching hospital. *American Journal of Medical Quality, 33*(5), 493-501. https://doi.org/10.1177/1062860617753063

Hughes, L. S., Phillips, R. L., Jr., DeVoe, J. E., & Bazemore, A. W. (2016). Community vital signs: Taking the pulse of the community while caring for patients. *Journal of the American Board of Family Medicine*, *29*(3), 419-422. https://doi.org/10.3122/jabfm.2016.03.150172

Institute for Healthcare Improvement. (2020). *The IHI Triple Aim Initiative*. http://www.ihi.org/Engage/Initiatives/TripleAim/Pages/default.aspx

Institute of Medicine. (2000). *Promoting health: Intervention strategies from social and behavioral research*. https://doi.org/10.17226/9939

James, C. V. (2019). *Actively addressing social determinants of health will help us achieve health equity*. https://www.cms.gov/blog/actively-addressing-social-determinants-health-will-help-us-achieve-health-equity

Kaplan, G. A. (1996). People and places: Contrasting perspectives on the association between social class and health. *International Journal of Health Services, 26*(3), 507-519. https://doi.org/10.2190/4CUU-7B3G-G4XR-0K0B

Kind, A. J., Jencks, S., Brock, J., Yu, M., Bartels, C., Ehlenbach, W., Greenberg, C., & Smith, M. (2014). Neighborhood socioeconomic disadvantage and 30-day rehospitalization: A retrospective cohort study. *Annals of Internal Medicine, 161*(11), 765-774. https://doi.org/10.7326/m13-2946

Kind, A. J. H., & Buckingham, W. R. (2018, Jun 28). Making neighborhood-disadvantage metrics accessible - The Neighborhood Atlas. *New England Journal of Medicine, 378*(26), 2456-2458. https://doi.org/10.1056/NEJMp1802313

Knighton, A. J., Savitz, L., Belnap, T., Stephenson, B., & VanDerslice, J. (2016). Introduction of an area deprivation index measuring patient socioeconomic status in an integrated health system: Implications for population health. *eGEMs, 4*(3), 1238. https://doi.org/10.13063/2327-9214.1238

Kolak, M., Bhatt, J., Park, Y. H., Padrón, N. A., & Molefe, A. (2020). Quantification of neighborhood-level social determinants of health in the continental United States. *JAMA Network Open, 3*(1), e1919928-e1919928. https://doi.org/10.1001/jamanetworkopen.2019.19928

Liaw, W., Krist, A. H., Tong, S. T., Sabo, R., Hochheimer, C., Rankin, J., Grolling, D., Grandmont, J., & Bazemore, A. W. (2018). Living in "cold spot" communities is associated with poor health and health quality. *Journal of the American Board of Family Medicine, 31*(3), 342-350. https://doi.org/10.3122/jabfm.2018.03.170421

Maroko, A. R., Doan, T. M., Arno, P. S., Hubel, M., Yi, S., & Viola, D. (2016). Integrating social determinants of health with treatment and prevention: A new tool to assess local area deprivation. *Preventing Chronic Disease, 13*, E128. https://doi.org/10.5888/pcd13.160221

Messer, L. C., Laraia, B. A., Kaufman, J. S., Eyster, J., Holzman, C., Culhane, J., Elo, I., Burke, J. G., & O'Campo, P. (2006). The development of a standardized neighborhood deprivation index. *Journal of Urban Health, 83*(6), 1041-1062. https://doi.org/10.1007/s11524-006-9094-x

Office of Disease Prevention and Health Promotion. (2020). *Determinants of health*. https://www.healthypeople.gov/2020/about/foundation-health-measures/Determinants-of-Health

Phillips, R. L., Liaw, W., Crampton, P., Exeter, D. J., Bazemore, A., Vickery, K. D., Petterson, S., & Carrozza, M. (2016). How other countries use deprivation indices—and why the United States desperately needs one. *Health Affairs, 35*(11), 1991-1998. https://doi.org/10.1377/hlthaff.2016.0709

Singh, G. K. (2003). Area deprivation and widening inequalities in US mortality, 1969-1998. *American Journal of Public Health, 93*(7), 1137-1143. https://doi.org/10.2105/ajph.93.7.1137

Singh, G. K., & Lin, C. C. (2019, Jul 16). Area deprivation and inequalities in health and health care outcomes. *Annals of Internal Medicine, 171*(2), 131-132. https://doi.org/10.7326/m19-1510

Walker, R. J., Smalls, B. L., Campbell, J. A., Strom Williams, J. L., & Egede, L. E. (2014). Impact of social determinants of health on outcomes for type 2 diabetes: A systematic review. *Endocrine, 47*(1), 29-48. https://doi.org/10.1007/s12020-014-0195-0

Weeks, W. B., Cao, S. Y., Lester, C. M., Weinstein, J. N., & Morden, N. E. (2020). Use of Z-codes to record social determinants of health among fee-for-service Medicare beneficiaries in 2017. *Journal of General Internal Medicine, 35*(3), 952-955. https://doi.org/10.1007/s11606-019-05199-w

Weich, S., Twigg, L., Lewis, G., & Jones, K. (2005). Geographical variation in rates of common mental disorders in Britain: Prospective cohort study. *British Journal of Psychiatry, 187*, 29-34. https://doi.org/10.1192/bjp.187.1.29

White, J. S., Hamad, R., Li, X., Basu, S., Ohlsson, H., Sundquist, J., & Sundquist, K. (2016). Long-term effects of neighbourhood deprivation on diabetes risk: Quasi-experimental evidence from a refugee dispersal policy in Sweden. *Lancet Diabetes Endocrinology, 4*(6), 517-524. https://doi.org/10.1016/s2213-8587(16)30009-2

Wilkinson, G. W., Sager, A., Selig, S., Antonelli, R., Morton, S., Hirsch, G., Lee, C. R., Ortiz, A., Fox, D., Lupi, M. V., Acuff, C., & Wachman, M. (2017). No equity, no Triple Aim: Strategic proposals to advance health equity in a volatile policy environment. *American Journal of Public Health, 107*(S3), S223-S228. https://doi.org/10.2105/ajph.2017.304000

Winkleby, M., Sundquist, K., & Cubbin, C. (2007). Inequities in CHD incidence and case fatality by neighborhood deprivation. *American Journal of Preventive Medicine, 32*(2), 97-106. https://doi.org/10.1016/j.amepre.2006.10.002

Xiao, Q., Berrigan, D., & Matthews, C. E. (2017). A prospective investigation of neighborhood socioeconomic deprivation and self-rated health in a large US cohort. *Health Place, 44*, 70-76. https://doi.org/10.1016/j.healthplace.2017.01.003

Zammit, S., Lewis, G., Rasbash, J., Dalman, C., Gustafsson, J. E., & Allebeck, P. (2010). Individuals, schools, and neighborhood: A multilevel longitudinal study of variation in incidence of psychotic disorders. *Archives of General Psychiatry, 67*(9), 914-922. https://doi.org/10.1001/archgenpsychiatry.2010.101

Zeitlin, J., Combier, E., Levaillant, M., Lasbeur, L., Pilkington, H., Charreire, H., & Rivera, L. (2011). Neighbourhood socio-economic characteristics and the risk of preterm birth for migrant and non-migrant women: A study in a French district. *Paediatric Perinatal Epidemiology, 25*(4), 347-356. https://doi.org/10.1111/j.1365-3016.2011.01201.x