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# Uses of Social Determinants of Health Data to Address Cardiovascular Disease and Health Equity: A Scoping Review

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**BACKGROUND:** Cardiovascular disease is the leading cause of morbidity and mortality worldwide. Prior research suggests that social determinants of health have a compounding effect on health and are associated with cardiovascular disease. This scoping review explores what and how social determinants of health data are being used to address cardiovascular disease and improve health equity.

**METHODS AND RESULTS:** After removing duplicate citations, the initial search yielded 4110 articles for screening, and 50 studies were identified for data extraction. Most studies relied on similar data sources for social determinants of health, including geocoded electronic health record data, national survey responses, and census data, and largely focused on health care access and quality, and the neighborhood and built environment. Most focused on developing interventions to improve health care access and quality or characterizing neighborhood risk and individual risk.

**CONCLUSIONS:** Given that few interventions addressed economic stability, education access and quality, or community context and social risk, the potential for harnessing social determinants of health data to reduce the burden of cardiovascular disease remains unrealized.

**Key Words:** cardiovascular disease ■ data-driven interventions ■ health equity ■ hypertension ■ social determinants of health



Cardiovascular disease (CVD) is the leading cause of morbidity and mortality across the world, accounting for 32% of deaths worldwide.[1] In the United States alone, CVD accounts for 659000 annual deaths, and costs the nation $219 billion each year.[2] Key risk factors for CVD include high blood pressure, high cholesterol, and smoking, with other medical conditions and lifestyle choices such as diabetes, obesity, poor diet, physical inactivity, and excessive alcohol use increasing one's risk.[2] Nationwide, 7% of men and 4.2% of women have CVD, with the highest prevalence among adults ≥75 years of age.[3] Racial and ethnic disparities in CVD are also well documented.[4] Moreover, the risk incurred by low socioeconomic status alone is comparable to traditional risk factors.[5]

The Centers for Disease Control and Prevention (CDC) and the American Heart Association have identified the need to address social determinants of health (SDOH) in both public health and in health care delivery efforts to close these gaps between population groups.[6,7] Furthermore, practicing clinicians have called for the integration of SDOH, big data, and technology to address CVD disparities, specifically calling for an integration that must reach beyond the

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## CLINICAL PERSPECTIVE

### What Is New?

- Previous reviews have examined the role of social determinants of health (SDOH) influence on cardiovascular disease (CVD) outcomes; however, these reviews have been limited to specific SDOH factors and have not examined all SDOH domains in 1 review.
- Reviews on a wide range of SDOH factors lacked focus on CVD outcomes or focused on 1 approach to using big data to address CVD outcomes or health equity (such as solely reviewing applications of artificial intelligence algorithms), rather than exploring the range of approaches.
- This review addresses these gaps in evidence by examining what and how data across sectors are being used to address social determinants of health to improve equity in CVD outcomes.

### What Are the Clinical Implications?

- This review discusses the ways in which SDOH data may be applied in clinical settings, as many studies discussed in this review are performed within a clinical or hospital setting, and link electronic health record data with SDOH data to generate health equity reports, construct patient care plans, form risk scores for clinical decision making, and improve patient self-management of CVD outcomes.
- The COVID-19 pandemic has exacerbated underlying disparities in health care, and patients who have contracted COVID-19 are at a higher risk for CVD, indicating the importance of applying the findings of this review to address these developing needs.

### Nonstandard Abbreviations and Acronyms

| | |
|---|---|
| **CDC** | Centers for Disease Control and Prevention |

health care system and into the community and patients' homes.[8–11] According to the CDC, there are 5 SDOH domains that must be addressed to improve health: economic stability, education access and quality, health care access and quality, neighborhood and built environment, and social and community context.[7] Social and community context includes the existence of discrimination, which is a threat to health among racial and ethnic minority communities.[12] Further research has linked the effects of these domains to CVD outcomes.[5,8–11,13–21]

Despite the literature documenting the association of SDOH and CVD outcomes, efforts to address SDOH have been hindered by lack of knowledge about how SDOH compounds problems of access and treatment, as well ways in which SDOH may be practically addressed. A major obstacle for addressing these issues has been an absence of strategies to harness data about SDOH to drive interventions, especially because data may come from many different sectors.[22]

The goal of this scoping review is to assess what types of SDOH data are being used to reduce the burden of CVD and how these data are being applied. Previous reviews have examined the role of SDOH on influencing CVD outcomes; however, these reviews have been limited to specific SDOH domains (such as housing instability and food insecurity, or education and income) and have not examined the all SDOH factors that influence health in 1 review.[23,24] Other reviews have focused on a wide range of SDOH, yet either lacked focus on CVD or only evaluated single methodological approaches to analyze data.[25,26] This review addresses these gaps in evidence by focusing on the ways in which SDOH data have been applied to improve CVD outcomes, largely in the United States but also in other high-income countries.

## METHODS

### Search Strategy

Search terms for each of the 3 domains of interest, social determinants of health, data, and CVD, were used to retrieve abstracts from PubMed, Web of Science, Cumulative Index to Nursing and Allied Health Literature, Ovid/Embase, Cochrane, and Scopus. Search terms for each of the areas of interest included both the domain (eg, social determinants of health) as well as *Medical Subject Headings* and other terms related to these domains (eg, social environment, social inequality, living environment). Following the World Health Organization's definition of CVD, we included search terms that included heart and blood vessel disorders, and health conditions and complications that are strongly associated with CVD such as diabetes, high cholesterol, hypertension, myocardial infarction, and stroke.[1] Although not a systematic review, this review conforms to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses protocol for scoping reviews.[27] Database searches were conducted on March 11, 2022, with results exported to the Covidence application.[28] In all, >60 terms were entered, with searches modified as needed for each database. In regard to the American Heart Association Transparency and Openness Promotion Guidelines on data sharing and study materials, no original data were produced by this scoping review; however, all search strategies may be found in Data S1. Additionally, because this review did not include human subjects, this review did not require institutional review board approval or patient written informed consent.

## Eligibility Criteria

We use the definition for CVD put forth by the World Health Organization, which defines CVD as heart and blood vessel disorders, and includes health conditions and complications that are strongly associated with CVD such as diabetes, high cholesterol, hypertension, myocardial infarction, and stroke.[1] The decision to include data from different domains was based on the recognition that multiple factors affect health outcomes.[29] This review only included studies located in high-income countries, as categorized by the World Bank.[30] The search results were limited to studies published in 2014 and onward, because health care providers were required to demonstrate meaningful use of electronic health records (EHRs) by January 1, 2014 under the American Recovery and Reinvestment Act.[31,32] At this time, there was a similar movement across the European Union. In 2013, the European Commission released a major report urging health care providers across the European Union to increase adoption of EHRs, and improved adoption was demonstrated over the next 5 years.[33,34] We excluded all studies with a study population <18 years of age and those in languages other than English. Editorials, commentaries, systematic reviews, conference abstracts, conference proceedings, methods articles, reviews, qualitative studies, articles discussing treatment protocols, and those intended to validate tools or software applications were also excluded.

## Screening and Study Selection

Inclusion criteria included studies that (1) contained data related to SDOH; (2) contained outcomes related to CVD; (3) included data from ≥1 of the SDOH domains as outlined by the CDC framework; (4) were located in high-income countries, as categorized by the World Bank[30]; and (5) were limited to studies published in 2014 to 2022, because US health care providers were required to demonstrate meaningful use of EHRs by January 1, 2014 under the American Recovery and Reinvestment Act, and a similar movement across the European Union was happening at the same time.[31–34] Articles must have been published between January 2014 and March 2022. Exclusion criteria included (1) studies with a study population <18 years of age and (2) those in languages other than English. Also excluded were editorials, commentaries, systematic reviews, conference abstracts, conference proceedings, methods articles, reviews, qualitative studies, articles discussing treatment protocols, and those intended to validate tools or software applications. The Figure summarizes the screening and study selection process.

## Data Extraction

We extracted results from included studies, and the following categories were extracted: authors, year, study purpose, and SDOH domain addressed by the study. The following additional categories were extracted: outcomes, outcome measures, data sources, and main findings. CVD-related results included outcomes (eg, stroke, hypertension) and outcome measures (eg, blood pressure values considered to be hypertension). Other information extracted included the data source (eg, health claims data, transportation data), how the data were being used or applied (eg, use of data to create vulnerability maps), and the time period covered by the data sources used. We also extracted the method or algorithm applied (eg, deep learning, machine learning) and the limitations/barriers to the data identified (eg, missing data). Notably, we excluded covariates from the data extraction.

# RESULTS

A complete extraction table of the studies may be found in Table S1.[35–84] The study characteristics are summarized in Table 1, the SDOH domains addressed by each study are summarized in Table 2, and the primary uses of the SDOH data among each study are summarized in Table 3.

## Study Characteristics

Table 1 outlines the characteristics of the studies selected for this review. The majority of studies analyzed were published in the years 2020 (n=8) and 2021 (n=8). Most articles studied populations within the United States (n=40), and New York City was the most common geographical location within the United States (n=8). Twelve studies were in nations outside the United States.

Common settings were uses of data within the hospitals (n=26), neighborhoods (n=13), and primary care practices (n=11). Populations of interest were health care users within a specific health care system (n=31). The second most common population was residents within a specific geographic area, such as residents of specific states or cities (n=19). Most studies used a cross-sectional study design (n=17), retrospective cohort studies (n=13), and geographical and spatial analysis (n=12), whereas less common study designs included case studies (n=3), clinical trials (n=3), and randomized control trials (n=2). Thirty-three studies used linear or logistic regression methods,[35,37–42,46–48,51,52,54,56–60,62,64–66,69–78,80,81]

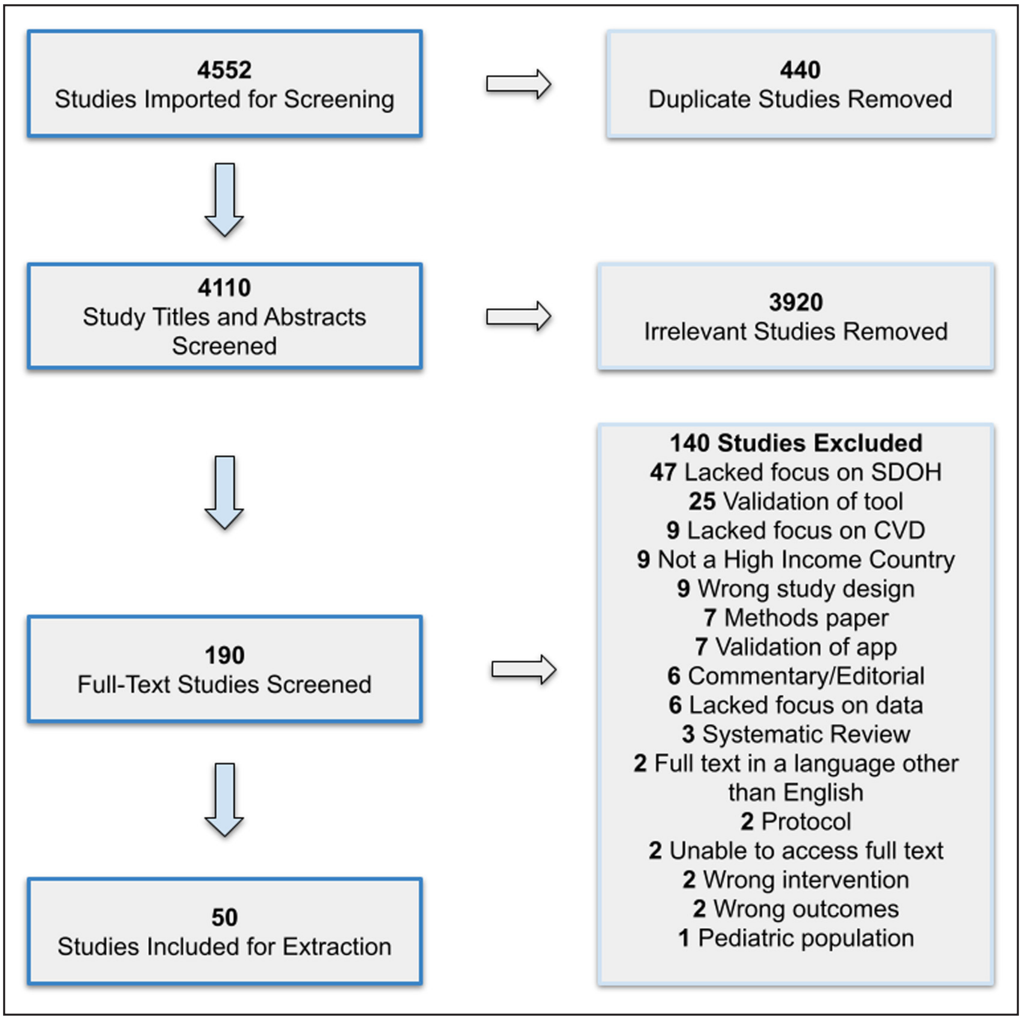


**Figure. The screening process flowchart.**
app indicates application; CVD, cardiovascular disease; and SDOH, social determinants of health.

and 14 studies applied spatial analysis to understand the relationship between SDOH and CVD outcomes.[35–38,45,50,53,54,58–61] Machine learning, including data mining, gradient boosting machine, extreme gradient boosting, phase type random forests, Breiman's random forest, support vector machine, and tree-based classification were used in 4 studies.[52,72,73,75]

Six types of outcomes were investigated. The most common outcomes studied were cardiac outcomes, such as acute heart events (n=13) and chronic disease (n=33). Thirty-one studies characterized patient lifestyles, 14 studies investigated decision-making improvement strategies, and 4 studies investigated patient management of CVD (Table 2). Thirteen studies examined acute heart events such as heart attack, stroke, hospitalization, readmission, and ejection fraction changes.[36,38,40,45,50,53,54,59,63–65,73,79] Thirty-three studies investigated chronic heart diseases such as high blood pressure, chronic heart disease, atherosclerotic CVD, and medication adherence.[35,41–44,46–48,51,52,55–58,60–62,67,68,70–72,74–78,80,84] Four studies investigated CVD mortality.[37,39,49,66]

## SDOH Domains Addressed by Each Study

Table 2 summarizes the SDOH domains addressed in these studies and the uses of the data. The most common SDOH domain among the articles retrieved was health care access and quality,[36,37,39–45,47,48,50,58,63,64,66,67,69–75,77–84] followed by the neighborhood and built environment.[35,46,49,52–61] Four studies measured economic stability as their primary domain.[38,62,65,68] Eleven studies addressed 2 SDOH domains, focusing on a combination of the economic stability, health care access and quality, or neighborhood and built environment domains.[37–39,45,49,58,62,64,73,75,76] One article addressed social and community context.[76] No studies captured in our review indicated a study purpose of addressing education access and quality.

**Table 1. Study Characteristics**

| Characteristics | Examples | References |
|---|---|---|
| Settings | | |
| Hospitals (n=26) | Calculating risk to improve physician decision making, evaluating the distribution of medication prescriptions. | 36–38,40,41,43,44,47,48,50,54,55,59,62–66,70–75,79,80 |
| Neighborhoods (n=13) | Community-based interventions, characterizing a neighborhood's risk, understanding access to health care. | 35,42,45,46,49,51,52,56,57,61,69,81,82 |
| Primary care practices (n=11) | Hypertension management in primary care settings, health equity audits among primary care offices, applying interventions in primary care settings. | 39,53,58,60,67,68,76–78,83,84 |
| Populations | | |
| Health care users within a system (n=31) | Patients who had used health care from specific systems, offices, or hospitals. | 37,38,40,41,43,44,46–48,50,54,55,58,59,62–66,70–76,78–80,83,84 |
| Specific neighborhoods or geographic areas (n=19) | Individuals who live in specific neighborhoods (such as New York City housing) or state. | 35,36,39,42,45,49,51–53,56,57,60,61,67–69,77,81,82 |
| Study design | | |
| Cross-sectional (n=17) | Characterizing neighborhoods, evaluating the effects of an intervention, calculating risk. | 42,49,51,52,54–56,62,63,67–69,71,73,76,77,81 |
| Retrospective cohort (n=13) | Observing the effects of climate change, the impact of an e-referral program, creating indexes, calculating risk. | 38,39,41,44,61,64–66,70,72,74,75,78 |
| Geographic or spatial analysis (n=12) | Mapping risk, access to care, or neighborhood characteristics. | 35–37,43,45–48,50,53,58,60 |
| Case studies (n=3) | Studying health registries in specific regions or nations. | 40,59,84 |
| Clinical trial (n=3) | Testing interventions in hospitals or primary care settings. | 79,80,82 |
| Randomized control trials (n=2) | Testing the impact of an intervention. | 57,83 |
| Analytic method | | |
| Regression (n=33) | Linear or logistic regression. | 35,37–42,46–48,51,52,54,56–60,62,64–66,69–78,80,81 |
| Spatial analysis (n=15) | Mapping access to care, mapping risk. | 35–38,43,45,50,53,54,58–61 |
| Machine learning (n=4) | Data mining, gradient boosting machine, extreme gradient boosting (eg, XGBoost), phase type random forests, Breiman's random forest, support vector machine, and tree-based classification. | 52,72,73,75 |
| Health outcomes investigated | | |
| Chronic heart disease (n=33) | High blood pressure, chronic heart disease, atherosclerotic cardiovascular disease, medication adherence. | 35,41–44,46–48,51,52,55–58,60–62,67,68,70–72,74–78,80,84 |
| Acute heart events (n=13) | Heart attack, stroke, hospitalization, readmission, ejection fraction changes. | 36,38,40,45,50,53,54,59,63–65,73,79 |

## Uses of SDOH Data

Table 3 summarizes the primary uses of SDOH data to address CVD outcomes and health equity. Data measuring an SDOH domain were used for 3 main purposes: neighborhood characterization, risk calculation, and intervention development (Table 3).

## Uses of SDOH Data to Characterize Neighborhoods

Unsurprisingly, SDOH data have been used to understand the relationship between the built environment and CVD outcomes. Twenty-seven studies used data to characterize neighborhoods. The most common sources of data were EHRs that were used to describe prevalence or incidence of CVD risk factors and outcomes at the neighborhood level. Data were used to understand the health status of neighborhoods, including barriers to health that individuals within a neighborhood may face. Pharmaceutical dispensing data and health literacy data harnessed in 1 study helped researchers identify distribution patterns and disparities in CVD medication dispensing within a neighborhood.[43] Specifically, this study mapped these data to reveal neighborhoods that had lower access to pharmacies and were unable to dispense the necessary CVD medications for self-management.[43] Data about the neighborhood and built environment were collected to create climate vulnerability maps that could impact CVD outcomes (n=2): 1 for heat-extreme events[35] and another for heat-extreme events and flooding.[49] One study applied EHR data to identify health care access patterns among veterans in New York City after a hurricane,[41] whereas another study analyzed the effects of perceived spatial stigma (for example, feeling social judgment for living in a low-income area) on CVD outcomes among individuals who live in an urban setting.[51] Additional studies (n=2)

**Table 2. SDOH Domains Addressed to Improve Cardiovascular Disease and Health Equity Outcomes**

| SDOH domains investigated | References |
|---|---|
| Health care access and quality (n=32) | 36,37,39–45,47,48,50,58,63,64,66,67,69–75,77–84 |
| Neighborhood and built environment (n=13) | 35,46,49,52–61 |
| Economic stability (n=4) | 38,62,65,68 |
| Social and community context (n=1) | 76 |
| Education access and quality (n=0) | … |
| Studies that addressed >1 domain | |
| Economic stability, neighborhood and built environment (n=2) | 38,62 |
| Economic stability, health care access and quality (n=3) | 39,64,75 |
| Health care access and quality, neighborhood and built environment (n=5) | 37,45,49,58,73 |
| Health care access and quality, social and community context (n=1) | 76 |

SDOH indicates social determinants of health.

evaluated the association of air pollution and CVD[55] or identified the health effects of highway-adjacent housing.[57] Police data, state health survey data, census data, and EHR data have been combined to identify the characteristics that influence CVD within a defined neighborhood.[46] Researchers applied spatial analysis (n=10) to identify access to emergency care and to applied health scores to identify risk within neighborhoods.[36,37,44,45,50,53,54,58,60,61]

Data have been used to understand the relationship between disease burden and the built environment. Three studies applied EHR data to New York City neighborhoods that experience higher chronic disease burden.[42,47,48] Specifically, hospital administrative data, emergency department data, and EHR data were used map public health surveillance (n=2) so that health care providers and policy makers could identify CVD health risk among neighborhoods.[47,48] One study observed the use of a regional health registry and identified the disparities within neighborhoods.[40] Health administrative data, census data, and food environment data have been compiled to create a county-level CVD risk score.[39] Three studies used social media X (formerly Twitter) data to characterize chronic conditions within a neighborhood and Google View satellite images to identify the neighborhood characteristics associated with CVD outcomes,[52,56,61] whereas another evaluated the spatial relationship between neighborhood disadvantage and major atherosclerotic CVD-related events to understand spatial risk of CVD.[38]

## Use of SDOH Data for Risk Calculation

Fifteen studies used data about ≥1 SDOH domain to evaluate risk scores that measure social risk. One study recalibrated the Veterans Affairs cardiac risk score, and found that EHR data are best for CVD risk prediction in comparison with the established risk score.[74] One study created an SDOH score (including covariates such as educational attainment, health literacy, stress, living arrangements, social isolation, census-based income, and ethnicity), and the Framingham Risk Score (a commonly used risk score to predict CVD over 10 years).[70] Administrative claims data, laboratory data, and demographic data were used to create a mortality risk score,[63] and 1 study determined that adding SDOH data strengthened a CVD risk prediction score.[64] Data were used to create a new measure of CVD risk that included allostatic load to understand the effects of racism on CVD.[76] One study used the Protocol for Responding To and Assessing Patients' Risks, Assets, and Experiences tool to evaluate patient SDOH needs (self-reported data on SDOH such as lack of housing, unemployment, and access to medicine or health care) to further understand the association between cardiometobolic risk and SDOH.[62] One study assessed the predictive power of a risk score for carotid artery stenosis.[71] Two studies assessed the Area Deprivation Index's ability to predict CVD risk,[65,66] whereas another evaluated the impact of health information technology on CVD risk prediction.[69]

Artificial intelligence has been applied to inform clinician and policy decision making on CVD risk,

**Table 3. Uses of SDOH Data to Address Cardiovascular Disease Outcomes and Improve Health Equity**

| Uses of SDOH data | Examples of data use | References |
|---|---|---|
| Neighborhood characterization (n=27) | Practice-level equity reports, electronic referral system to community-based interventions, individualized care plans, EHR reminders, improved health literacy, health coaching application, self-reported health application linked to EHRs, regional health registry. | 35–61 |
| Patient risk calculation (n=15) | Health registry, understand neighborhood access to health care after climate disaster, creating health indexes, identify neighborhoods with higher disease burden, identify neighborhood disadvantage, identify spatial distribution of risk and disease, medical dispensing patterns, characterizing risk, map emergency service access, public health surveillance. | 62–76 |
| Intervention development (n=8) | Practice-level equity reports, electronic referral system to community-based interventions, individualized care plans, EHR reminders, improved health literacy, health coaching application, self-reported health application linked to EHRs, health registry. | 77–84 |

EHR indicates electronic health record; and SDOH, social determinants of health.

detection, and treatment. For instance, to assure appropriate treatment of multiethnic patients and improve health care access, Sarraju et al applied machine learning techniques to create a 5-year prediction model of CVD among such patients using neighborhood location data.[72] Ye et al applied machine learning and EHR data to predict the incidence of hypertension within 1 year in 1.5 million Maine residents using socioeconomic indicators.[75] An additional study applied the Familial Hypercholesterolemia Case Ascertainment Tool algorithm to describe risks of familial hypercholesterolemia (and resulting ischemic heart disease) among ethnically diverse populations using prescription data as indicators for health care access.[67] One study applied machine learning to predict CVD hospital readmissions using environmental risk.[73]

## Use of SDOH Data for Intervention Development

Eight studies described intervention development to improve CVD outcomes by incorporating SDOH data. EHR data and health care administrative data have been used to create a health care registry to improve data interoperability, allowing researchers, policy makers, and health care providers to track health care delivery and identify disparities in health care access at the regional level.[84] One study linked a digital health application to EHRs to address health care access by improving medication adherence to health literacy and CVD outcomes,[83] whereas another used a different application to improve patient self-management of hypertension by providing a coach to help patients better understand physician instructions.[82] A third study provided health education to community members by offering community-based education and screening for dental care and hypertension to improve health literacy and self-management of CVD.[81] One study evaluated racial disparities in health care and used SDOH data on patients' cultural, racial, and ethnic beliefs and background to generate clinician reminders to discuss hypertension with patients to improve self-management.[80] Similarly, clinical and health registry data on health care access and quality have been accessed to provide primary care practices with health equity reports.[77] One study linked patient EHRs, self-reported patient SDOH data (such as primary language at home), and a bidirectional community intervention e-referral portal, allowing health care providers to refer patients to community-based interventions based on patient need and receive feedback on patient progress.[78] Finally, 1 study constructed an application that analyzed patient reported outcomes (mental and social well-being data) to generate individualized CVD care plans.[79]

# DISCUSSION

This scoping review has examined 3 broad domains of data, social determinants of health, and CVD. Numerous studies have demonstrated the association between CVD and the 5 SDOH domains: economic stability,[5] education access and quality,[18,19,85] social and community context,[20] health care access and quality,[21] and the neighborhood and built environment,[17] and practicing clinicians have called for the use of big data on SDOH to address CVD and health equity.[8–11] This review identified 50 articles that have used SDOH data to address these outcomes. SDOH data have been used to address health outcomes, yet gaps in research and application exist. Although many studies used multiple sources of data to address SDOH and cardiovascular outcomes, by and large, the studies used similar data sources, including *International Classification of Diseases, Ninth Revision and Tenth Revision* (*ICD-9* and *ICD-10*) codes from geocoded EHR data (n=33), national survey responses and census data (n=17), and data focused largely on health care access and equity. Overall, studies that addressed the domain of health care access and quality,[37,39,42,44,45,58,63,64,72–75,77–79,84] and neighborhood and built environment[46,52–56,60] were found to successfully predict or improve CVD outcomes. Studies that developed individual risk scores relied almost exclusively on EHR or health administrative data (n=4). For example, Ye et al calculated risk using EHR data to create a risk prediction model of incident hypertension, but did not draw on other data sources.[75] Additionally, Nobel et al created an Index of Cardiometabolic Health using EHR data.[76] A growing body of literature has indicated that a variety of data sources are needed to capture constructs that cannot be described by a single data source.[86–88] Although EHR data provide clinical information, details on other SDOH factors (such as food security or socioeconomic status) are not captured. Additionally, multiple sources of data are needed to limit bias.[86] For example, EHR data only capture those using the health care system; as a result, those without access are likely underrepresented. Despite calls for improved integration of multiple SDOH from policymakers, clinicians, and researchers, only a handful of studies examined the role of economic stability and social and community context. Although many studies included race and ethnicity, and educational attainment as covariates, no studies primarily focused on the SDOH domains of racism or education access and quality.

Occasionally, studies drew from a wide range of nonhealth sector data including transportation data, police data, and retail data. For example, 1 study performed by Kihal-Talantikite et al in Strasbourg, France assessed the neighborhood influences on the spatial distribution of myocardial infarction.[53] To understand a neighborhood's access to greenspace, this study integrated data on health care systems; transportation; greenspace and public parks; athletic equipment and facilities from city sports programs; civic and community environments; local businesses; the educational environment; vendors, such as alcohol and tobacco stores; and land use and land coverage.[53] These sources were combined with EHR data to create maps to assess the neighborhood influences on the spatial distribution of myocardial infarction.[53] However, such uses of multisector data sources were rare, suggesting an untapped potential to combine a wide array of data sources to examine SDOH, specifically within the United States.

Although many studies used race as a covariate or stratified populations by race, there is an absence of attention to racism, which has been found to be a determinant of health.[12] The studies captured here add to the growing body of research documenting health disparities among racial and ethnic minorities, but fall short of exploring the role of racism as a determinant and as a mechanism for explaining those disparities. More research is needed to measure and examine the role racism plays as a driver of cardiovascular health inequities, because the burden of CVD is higher among the Black population.[4] Similarly, although studies commonly include educational attainment as a covariate, the domain of education access and quality is a different construct, one not well measured by educational attainment. Although some studies examined health literacy, this construct is also different from education access and quality, and is part of the health access and quality SDOH domain according to the CDC.[29] This review identified 3 objectives in the use of data to address SDOH and improve CVD outcomes: neighborhood characterization, patient risk calculation, and intervention development. Efforts to calculate patient risk sought to incorporate the SDOH domains of health care access and quality and economic stability, whereas intervention development was limited to addressing health care access and quality. Efforts to characterize neighborhoods primarily focused on the SDOH domains of health care access and quality, as well as the neighborhood and built environment to address CVD outcomes. This is unsurprising, given that a core mission of health care systems is to provide health care intervention to improve population, or at least, patient health outcomes. However, health care providers, policymakers, and researchers should consider efforts to better understand and develop interventions that address the SDOH domains of neighborhood and built environment, economic stability, education access and quality, and social and community context, because these also affect health care access and quality. Although health care systems may view domains such as education or economic stability as beyond their mission, the literature is clear that these social determinants of health impact health outcomes. Health care systems should continue to screen patients for needs, offer SDOH support services, and refer them to community support to meet the needs under the other domains.

Notably, in the United States, several recent federal policy initiatives are aimed at supporting the collection and analysis of SDOH data.[89] In their new strategy for the Accountable Care Communities Model, which aims to assess the health-related social needs of beneficiaries, the Centers for Medicare and Medicaid Innovation requires new participants to both collect and report on data related to SDOH.[90] As part of their Uniform Data System Modernization Initiative, the Health Resources and Services Administration has allocated $90 million to support data-driven approaches for Federally Qualified Health Centers to identify and address health inequity, which includes the collection of patient-level SDOH data beginning in 2023.[89,91] Additionally, the Office of the National Coordinator for Health Information Technology aims to advance the use and interoperability of SDOH data within EHR systems through a variety of initiatives; this includes developing policies to address SDOH data interoperability, supporting states in building EHR systems for SDOH data, and helping integrate SDOH data into provider workflows.[89,92] These initiatives open up opportunities to address some of the gaps identified in this review including the use and integration of multiple sources of SDOH data from a broad range of sectors. In 2018, Europe established the Joint Action on Health Information, a project funded by the European Commission, to strengthen health system performance assessment and population health monitoring.[93] A similar policy implemented in the United States could include data from all 5 SDOH domains and improve assessment and monitoring of health initiatives across the nation.

In comparison with other published reviews, this review offers a review of all 5 SDOH domains in relation to CVD in the literature. Previous reviews focused on CVD have only addressed 1 to 2 specific domains.[23,24] Khaing et al established the connection between education, income, and CVD, but did not explore use of SDOH data.[23] Parekh et al studied the connection between food insecurity, housing instability, and CVD, but did not investigate the use of SDOH data to address these domains.[24] This review has determined the different ways SDOH data have been applied to address all 5 SDOH domains. Other reviews have evaluated a wide range of SDOH domains, yet lacked focus on CVD outcome or only examined specific methods (such as machine learning).[25,26] Kino et al found that the application of machine learning to understand SDOH has relied upon traditional methods such as surveys.[25] Zhao et al found that machine learning is able to incorporate complex SDOH data across all 5 domains.[26] This review, however, has a broader scope, including studies that apply different types methods to understand all 5 SDOH domains.

Like all studies, this study has limitations. Our exclusion of non-English articles may have resulted in missing important studies; however, given our focus on high-income countries, we expect this limitation to have had minimal impact on our analysis. SDOH are understood differently by different audiences; therefore, studies that included SDOH beyond those in the CDC framework may have been missed.[29] Additionally, our decision to exclude articles published before 2014 may have resulted in missing some relevant studies. Finally, articles that focused on the validation of tools or applications were eliminated; to the extent that the validation methods focused on interventions not reported elsewhere, these may have been missed.

## CONCLUSIONS

Data from each SDOH domain can be used to express the state of health among a population, allowing a multidimensional look into the everyday lives of a neighborhood, a population, or place. The widespread availability of data across sectors can provide a sharper understanding of the health needs at hand. Future research should focus on addressing additional SDOH domains, such as education access and quality, and social and community context, and must include measures of racism. Given the widening health disparities in the United States, now is the time to harness big data and new analytic tools to address health equity and improve CVD outcomes.

## ARTICLE INFORMATION

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None.

### Supplemental Material

Data S1
Table S1

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