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Review

Social determinants of health in electronic health records and their impact on analysis and risk prediction: A systematic review

Min Chen [iD],[1] Xuan Tan[1] and Rema Padman[2]

[1]Department of Information Systems and Business Analytics, College of Business, Florida International University, Miami, Florida, USA, and [2]The H. John Heinz III College of Information Systems and Public Policy, Carnegie Mellon University, Pittsburgh, Pennsylvania, USA

Corresponding Author: Min Chen, Department of Information Systems and Business Analytics, College of Business, Florida International University, 11200 SW 8th Street, Miami, FL 33199, USA; min.chen2@fiu.edu

ABSTRACT

Objective: This integrative review identifies and analyzes the extant literature to examine the integration of social determinants of health (SDoH) domains into electronic health records (EHRs), their impact on risk prediction, and the specific outcomes and SDoH domains that have been tracked.

Materials and Methods: In accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, we conducted a literature search in the PubMed, CINAHL, Cochrane, EMBASE, and PsycINFO databases for English language studies published until March 2020 that examined SDoH domains in the context of EHRs.

Results: Our search strategy identified 71 unique studies that are directly related to the research questions. 75% of the included studies were published since 2017, and 68% were U.S.-based. 79% of the reviewed articles integrated SDoH information from external data sources into EHRs, and the rest of them extracted SDoH information from unstructured clinical notes in the EHRs. We found that all but 1 study using external area-level SDoH data reported minimum contribution to performance improvement in the predictive models. In contrast, studies that incorporated individual-level SDoH data reported improved predictive performance of various outcomes such as service referrals, medication adherence, and risk of 30-day readmission. We also found little consensus on the SDoH measures used in the literature and current screening tools.

Conclusions: The literature provides early and rapidly growing evidence that integrating individual-level SDoH into EHRs can assist in risk assessment and predicting healthcare utilization and health outcomes, which further motivates efforts to collect and standardize patient-level SDoH information.

Key words: social determinants of health, electronic health records, behavioral determinants, social factors, systematic review, risk prediction

INTRODUCTION

Social determinants of health (SDoH) are "conditions in which people are born, grow, live, work, and age,"[1] and they involve "the complex, integrated, and overlapping social structures and economic systems that are responsible for most health inequalities."[2,3] Healthy People 2020 organizes SDoH around 5 key domains: (1) economic stability, (2) education, (3) health and health care, (4) neighborhood and built environment, and (5) social and community context.[4] As

population health becomes an important focus of health care delivery, SDoH are increasingly seen as critical factors for identifying potential upstream drivers of poor outcomes and higher costs.[5,6] While these are often conflated with social risk factors, which are disadvantageous social conditions that may result in poor health outcomes,[7] this review addresses social and behavioral determinants that affect everyone. With SDoH information, it is anticipated that health systems and professionals can classify the complexity of their patients, identify appropriate interventions to meet various needs, and transform care with integrated services and community partnerships to improve health outcomes and reduce health disparities, while saving costs.[8–11]

The digitization of clinical records presents a new opportunity to integrate SDoH into electronic health records (EHRs) to enhance care delivery and population health.[12,13] The 2009 U.S Health Information Technology for Economic and Clinical Health Act incentivized the adoption of EHRs throughout the country. Today, virtually all hospitals and nearly 9 in 10 office-based physicians have adopted an EHR.[14,15] With widespread adoption of EHRs, policy is now shifting toward the use of EHR technology in a meaningful manner. Meaningful use criteria were implemented by the Medicare and Medicaid EHR Incentive Programs (now known as the Promoting Interoperability Programs) in 3 time-bound phases. Beginning in 2011, the first 2 stages emphasized capturing data (eg, patients' medical history, medication orders, vital signs, laboratory results, radiology reports, physician and nurse notes) and optimizing clinical workflows, respectively. The third stage, in 2017, called for all hospitals and eligible healthcare professionals to demonstrate continuous quality improvement of care and elimination of healthcare inequality across all groups.[16,17] The integration of SDoH into EHR systems will be central for healthcare institutions to meet Stage 3 objectives and avoid reductions to their Medicare payments for failing to do so.[13] More and more, health institutions and clinicians are exploring how to capture data related to social determinants in their EHRs and how to incorporate SDoH-related referral and intervention into routine care, with the goal to assess their quality performance and manage the health of not only individual patients but also of populations.[18–21]

EHRs systematically collect clinical information about patients such as medical history, vital signs, laboratory tests and results, and medication orders. Nonclinical determinants of health can manifest in the structured data elements such as age, race, ethnicity, and diagnosis codes (eg, homelessness). Some EHRs also have a few lifestyle domains, such as preferred languages, smoking and alcohol use, in a structured format.[22] Information on selected environmental and social domains such as housing, social support, and financial resource strain may also be extracted from EHRs' unstructured data (eg, free-text physician and nurse notes).[22] Yet, EHR-derived SDoH data are not sufficient to constitute a complete and accurate set of SDoH domains, and many social and behavioral determinants that may influence health and mortality are not captured. The expansion beyond the traditional clinical information collected in EHRs to include SDoH data requires the identification of what SDoH data to collect and how and when to collect them, and identifying the extent to which the SDoH data collected can be used in risk prediction and interventions to improve outcomes, such as collecting accurate and complete data on patients' living arrangements and economic stability (2 major domains of SDoH) in predicting the risk of 30-day hospital readmission.[23]

Prior literature reviews have explored the effectiveness of interventions targeting SDoH[24–26] or the evidence relating to screening

for the SDoH in clinical care setting[27]; however, none have explicitly examined the integration of SDoH into EHRs for the purposes of risk prediction and associated analytics. Other systematic reviews have focused on either a specific domain of SDoH such as food insecurity,[28] or interventions to improve SDoH among specific disadvantaged groups[29]; or on specific health outcomes, such as type 2 diabetes,[30] pregnancy among young people,[31] and adult all-cause mortality.[32] Noteworthy results from these systematic reviews illustrate a dearth of generalizable high-quality evidence on the impact of SDoH interventions in the context of population and public health. In perhaps the closest analog to our work, Golembiewski et al[33] conducted a rapid review that was limited to U.S.-based articles published between January 2010 and April 2018 and characterized the extent to which existing research has combined nonclinical data derived from external sources with different clinical datasets. Owing to the rapid growth in adoption of EHRs and the pressing needs in the meaningful use of EHRs as a tool to improve health outcomes, it is essential to better understand the type of determinants, data sources, and measures used effectively in the new context of prediction-assisted, EHR-enabled care delivery.

The purpose of this study is to review and analyze the currently available literature to determine whether SDoH can affect health outcomes through risk prediction and targeted intervention, and which SDoH domains have been tracked in the context of EHRs. We are interested in examining quantitative evidence regarding how SDoH may affect various outcomes that have important implications for healthcare cost and quality, such as disease diagnosis, use of healthcare services, referral and other interventions targeted at SDoH and risk of ER visits, and hospital admission or readmissions. To inform efforts to create national standards for representing SDoH information in EHRs, we also analyze the sources and tools used in the studies to collect and screen domains related to SDoH.

MATERIALS AND METHODS

Search strategy
We followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines[34] and the PRISMA-Equity 2012 extension for systematic reviews with a focus on health equity[35] to conduct our systematic review. The published literature was searched using strategies created with the help of a university librarian for studies that utilized SDoH in the EHR context. The search strategies were established using a combination of standardized terminologies, keywords, and MeSH (Medical Subject Headings). We aimed to be broad and inclusive by adapting wording of SDoH, such as socioeconomic factors, behavioral factors, nonclinical determinants, health disparity, etc. To verify our coverage of all relevant articles, we also compiled an inclusive list of social and behavioral determinants of health measures to search in the literature based on the conceptual frameworks proposed by the World Health Organization and the U.S. Centers for Disease Control and Prevention, and the nonclinical determinants of health measures used in the existing literature review.[33]

Table 1 shows the domains and dimensions of the health determinants we cover in the review, and the specific measures of these domains and dimensions can be found in Supplementary Table S1.

Data sources and searches
We queried PubMed (1948-present), CINAHL (1937-present), PsycINFO (1998-present), EMBASE (1947-present), and Web of Sci-

Table 1. Examples of search domains and dimensions

Domains	Dimensions
Economic stability	Income, financial resource, employment, basic needs
Neighborhood and built environment	Transportation, neighborhood, living arrangements, food access, environmental conditions
Health and health care	Insurance status, behavioral health, mental health
Education	Education, language
Social and community context	Race/ethnicity, social connections, other status, marital status

ence (1965-present) all through July 15, 2019, then updated on March 31, 2020. We intentionally made the search query as broad as possible to make sure that we extract as many results as possible related to the research questions posed in this systematic review. A total of 6687 articles were identified by searching the databases based on the different variations of EHRs and a combination of the standardized SDoH terminologies and keywords representing specific social and behavioral determinants of health (Supplementary Table S1). Duplicate records were identified using the automatic duplication finder in Mendeley[36] and Rayyan[37] online review software. We removed 361 duplicates using Mendeley and identified 26 more duplicates using Rayyan, ending up with 6300 unique studies for further screening.

Study selection

To be eligible for inclusion, published research had to meet all of the following 4 criteria:

1. Peer-reviewed research with full text published in English.
2. Integrated SDoH information into EHRs.
3. Examined the impact of integrating SDoH into EHRs.
4. Quantitative analysis.

Articles were excluded in 2 stages: a title and abstract review (6157 excluded) and then a full-text review of 143 articles (74 excluded). Studies excluded from the title and abstract screening included (1) systematic reviews/meta-analyses; (2) opinions, commentaries. perspectives, vision articles, guidelines, and protocol articles; (3) qualitative studies; (4) exploratory, conceptual studies; (5) studies prior to 2000; and (6) non–English language studies. During the full-text screening, we excluded conference posters and studies that did not focus on examining the impact of integrating SDoH into EHRs on analysis and risk prediction. This resulted in 69 articles for inclusion. We then used a snowballing technique whereby we searched the reference lists of included articles to identify potentially missed studies that should be considered and searched for the gray literature. We repeated this process on each additional article until no additional articles worthy of inclusion could be identified. This manual search process resulted in 2 more studies added to the pool. At each stage, we resolved conflicts in inclusion or exclusion by discussion and achieving consensus among the 3 independent reviewers. Figure 1 presents our search and screen process.

Data extraction and synthesis

From each selected article, we extracted a list of data elements determined by the research team such as year of publication, country of origin, data source, sample size, and level of SDoH measures used, how SDoH information is integrated into EHRs, outcome measures, study method, study purpose, findings, and limitations. Given the heterogeneity within included studies, as well as the lack of standardized or consistent reporting of SDoH domains and outcome measures, meta-analysis was not possible. Therefore, we used narrative synthesis to integrate our findings into descriptive summaries for SDoH and their impact on analysis and risk prediction.

RESULTS

Overall characteristics of the reviewed studies

We have summarized the characteristics of the 71 included studies in Table 2. Overall, the literature on integrating SDoH into EHRs is quite new but growing rapidly. All included studies were published between 2008 and 2020, with the majority from 2017 to 2020 (53 studies, or 75%). Most of the studies (68%) were from the United States, and all but 2 studies were from developed countries (Figure 2). There are 2 major approaches reported in the studies to acquire SDoH data: (1) merging SDoH information from external data sources into EHRs and (2) extracting SDoH information from unstructured clinical notes in the EHRs. A total of 56 of the 71 (79%) studies merged SDoH information from external data sources into EHRs, and the most frequently used external data sources were the publicly accessible American Community Survey (ACS) and the U.S. Census. While both the ACS and census data provide neighborhood level SDoH information, the ACS provides more up-to-date information about the social and economic needs of the community at the census-tract or ZIP code level every 5 years and releases estimates at the regional, state, and county levels every year.[38] Other studies that merged SDoH into the EHRs used commercial databases such as Nielsen Prime Location[39] and the Esri Business Analyst Premium product,[40] or initiated their own patient-level health surveys, as in Wagaw et al,[41] or community information system, as in Comer et al.[42]

Most existing literature (58 studies, or 82%) examined the association between SDoH and outcomes. These studies vary in terms of sample size (from a few hundred to over 6 million observations), region (including a dozen countries), and level of SDoH data (ie, neighborhood-level ACS or census data, individual-level SDoH data extracted from EHRs, and both). However, they all confirmed that SDoH was to some extent associated with outcomes. They found either that better SDoH measures were associated with decreased disease incidence[39,43] or improved health intervention[44] or that social disadvantages were associated with screening[45] or diagnosis,[46] use of referral services,[47] and adverse health outcomes.[48,49]

Social and behavioral determinants and risk factors

It is important to note that social (and behavioral) risk factors are sometimes conflated with social (and behavioral) determinants in the rapidly evolving literature. While SDoH affect anyone for better or worse, social risk factors are specific adverse social conditions (eg, homeless, social disadvantage) that are associated with poor health. Further, social risk factors and behavioral risk factors (eg, smoking, lack of exercise) are not the same but can be intertwined. Alderwick and Gottlieb[7] provided a timely SDoH lexicon for health
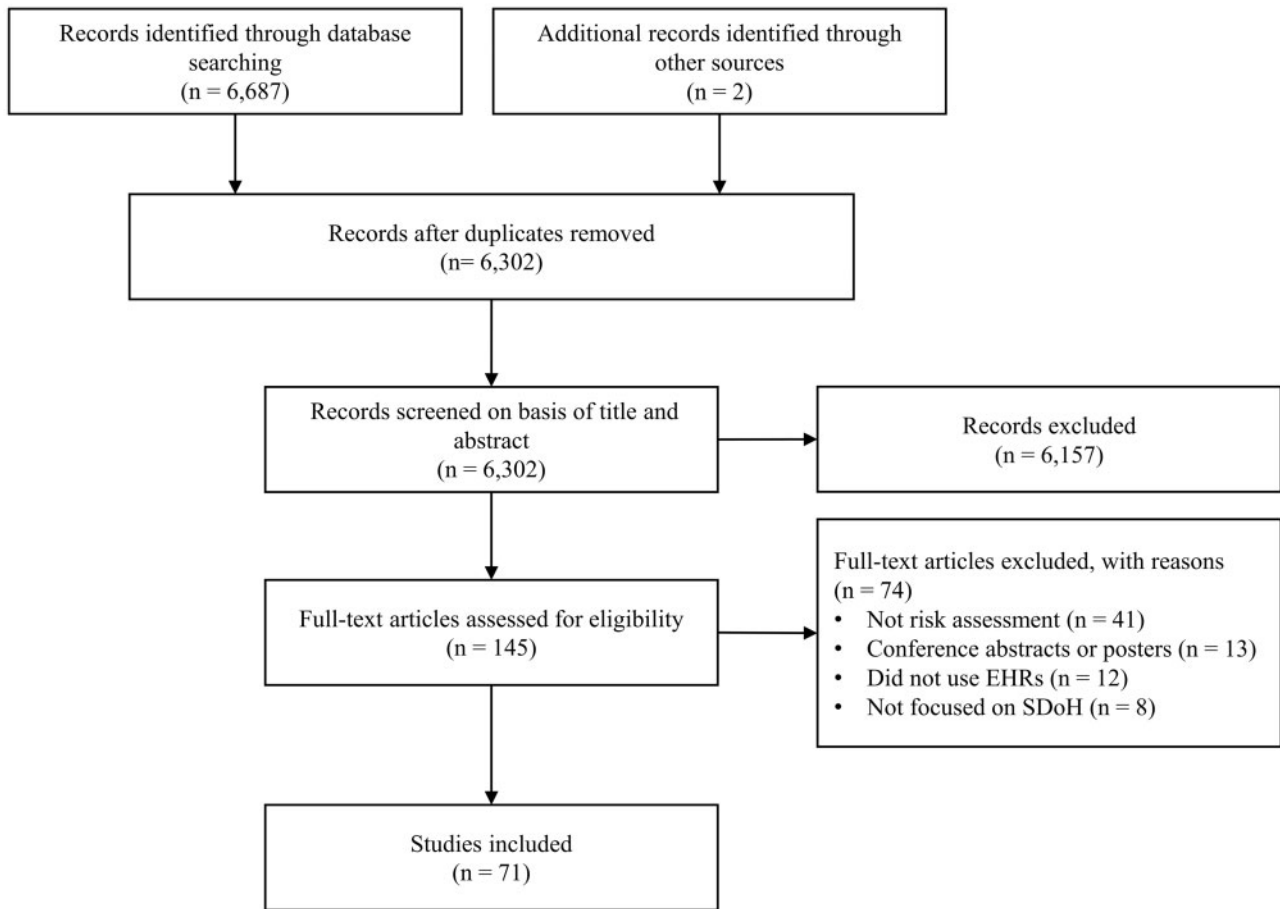
Figure 1. Flowchart of literature search and screening process. EHR: electronic health record; SDoH: social determinants of health.

Table 2. Characteristics and frequency distribution of the 71 reviewed studies

Characteristics	n	%
Publication year		
2017-2020	53	75
2008-2016	18	25
Major SDoH data source		
ACS or census	32	45
Other health surveys or databases	24	34
EHRs	15	21
SDoH level		
Neighborhood	41	58
Individual	25	35
Both	5	7
Sample size		
<10 000	24	34
Between 10 000 and 100 000	21	30
>100 000	26	37
Outcome		
Disease incidence/diagnosis/health outcome	41	58
Use of healthcare services	27	38
Referral/intervention/prevention of health services	3	4
Type of article		
Association	58	82
Prediction	13	18

ACS: American Community Survey; EHR: electronic health record; SDoH: social determinants of health.

care systems. We analyzed the included articles to show how the different terms are utilized in the literature, both as distinct categories as well as intertwined with each other (Figure 3). A total of 68% of the included studies examined SDoH and 6% examined social risk factors. Among the rest of the included studies (26%), 8% examined both social and behavioral determinants of health, another 8% examined SDoH and behavioral risk factors, and 10% examined both social risk factors and behavioral risk factors. Supplementary Table S3 shows the articles that fall into the distinct and intertwined categories. As healthcare initiatives and literature related to the SDoH grow rapidly, greater awareness of this conflation and clarity on key terms and the concepts underlying them could lead to more appropriate usage in future studies and practices.

Added contribution of SDoH in prediction

Thirteen recent articles explicitly examined whether integrating SDoH data into the EHRs can improve risk assessment, prediction, or interventions that address social determinants (Table 3). A total of 85% of these 13 articles were published between 2017 and March 2020. All but 1 study that merged external neighborhood-level SDoH data into the EHRs reported minimum contribution to predictive performance in any of their predictive models, including the prediction for SDoH-related service referrals,[50] repeat ED visits,[51] hospitalizations, hospital readmissions, and other use of healthcare services.[52–54] The only exception found that neighborhood poverty rate was a significant predictor of nonadherence to scheduled
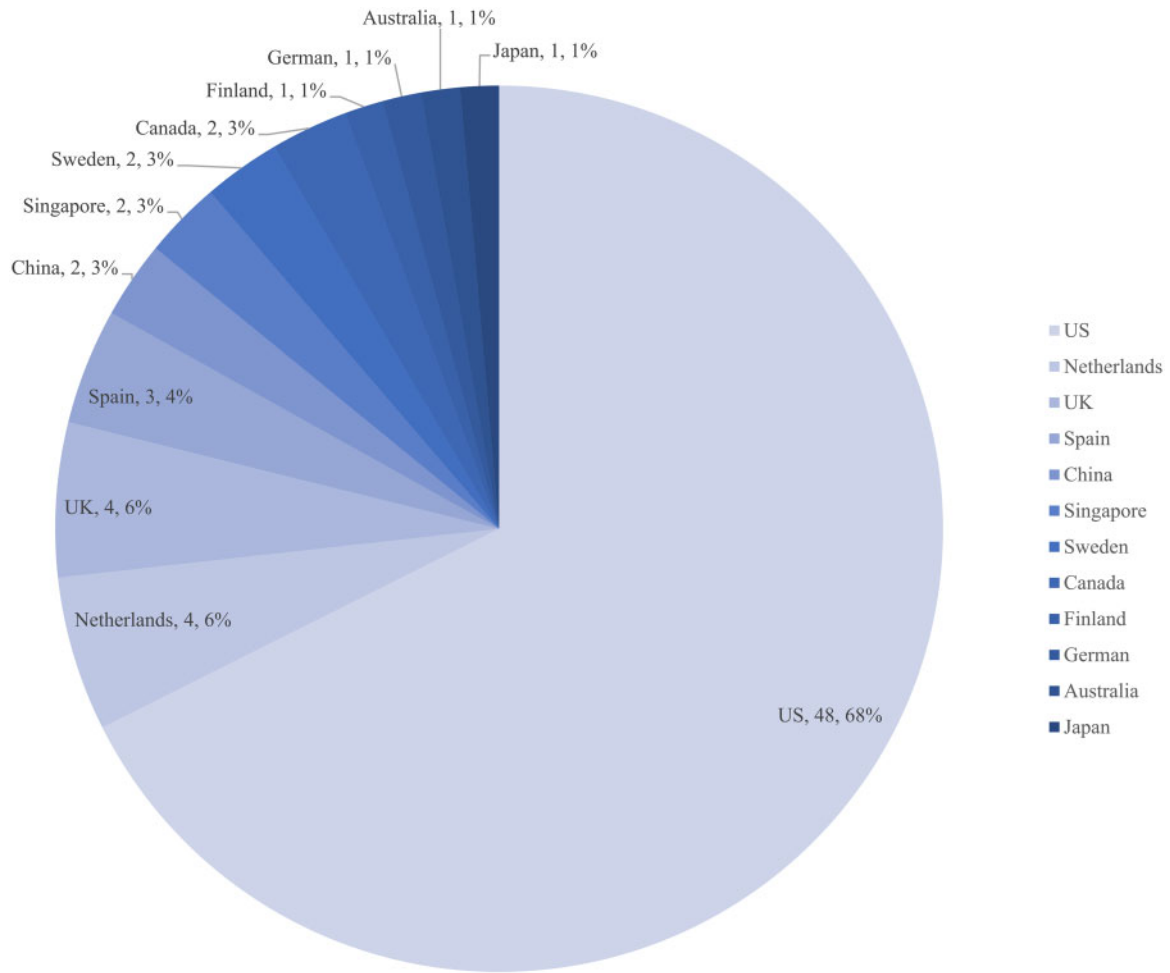
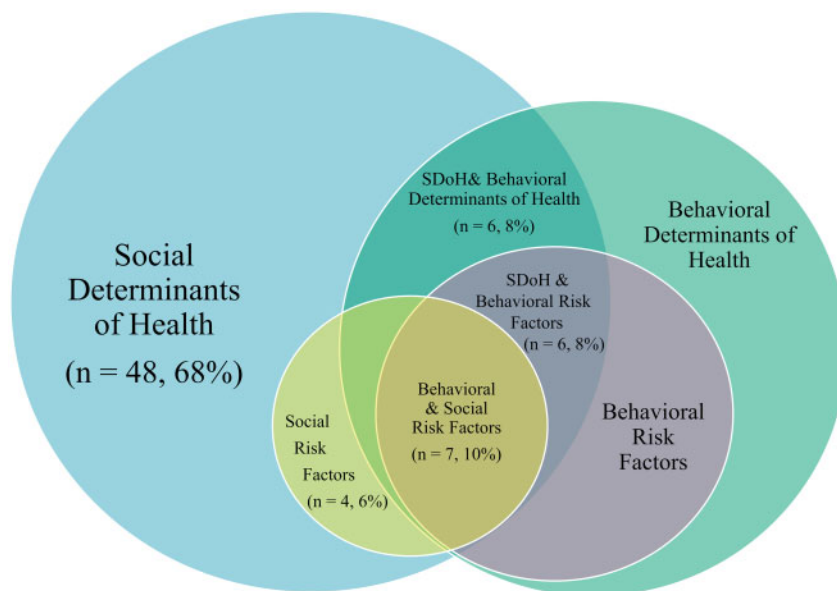**Figure 2.** Breakdown of the 71 included articles by country.

Figure 3. Classification of the 71 included articles by coverage. SDoH: social determinants of health.

Table 3. Characteristics of the 13 articles on using SDoH for risk prediction

Characteristics	n	%
Publication year		
2017-2020	11	85
2012-2016	2	15
Major SDoH data source		
ACS or Census	6	46
Other health surveys or databases	2	15
EHRs	5	38
SDoH level		
Neighborhood	6	46
Individual	5	38
Both	2	15
Sample size		
<10 000	5	38
Between 10 000 and 100 000	2	15
>100 000	6	46
Outcome		
Disease incidence/diagnosis/health outcome	3	23
Use of healthcare services	8	62
Referral/intervention/prevention of health services	2	15
SDoH contribution to improved prediction		
Contributed	8	62
Minimal contribution	5	38

ACS: American Community Survey; EHR: electronic health record; SDoH: Social Determinants of Health.

screening colonoscopy in multivariate modeling.[55] In contrast, the studies that incorporated individual-level SDoH data all reported significantly improved performance, in referrals to a social worker,[56] medication adherence,[57] risk of hospitalization[58] and 30-day rehospitalizations,[23] predicted performance of HIV risk assessment,[59] and suicide attempts.[60,61]

In summary, the results of our systematic review confirmed that various SDoH measures are associated with health outcomes. However, recent studies that assess whether knowledge of SDoH improves population risk assessment find that linking neighborhood-level (eg, census tract or ZIP code level) information on SDoH may not contribute much more to risk prediction above and beyond what is already provided by the EHR data. It could be due to the lack of variation in demographic characteristics,[62] given that these studies are mostly limited to data from a single or 2 EHR systems in 1 geographic region. On the other hand, natural language processing improved predictive models by extracting terms in clinical text indicative of high-risk factors.[63–65] Such automated risk prediction methods could leverage longitudinal EHRs alone for population risk assessment and catalyze targeted screening programs, as compared with costly and labor-intensive universal screening.

Table 3. Characteristics of the 13 articles on using SDoH for risk prediction

DISCUSSION

SDoH-EHR integration challenges

EHRs offer tremendous potential to aggregate, analyze, and integrate individual- and community-level data across settings and over time. Integrating SDoH into EHRs can provide a broader perspective on potential drivers of a patient's health status and can help identify both upstream and downstream approaches for improving the effectiveness of care. There is rapidly growing research on evaluating the impact of both community-level and individual-level SDoH integration in prediction modeling to improve health outcomes and resource utilization.

Information on community-level determinants such as poverty, unemployment, and even air pollution rates is generally available as structured data from the U.S. Census Bureau or other agencies.[39,40,66] However, analysis of existing literature shows that such community-level SDoH contributes minimally to the prediction performance, with 1 exception in recent literature that showed a significant impact of neighborhood poverty rate on colonoscopy screening.

While individual-level SDoH data have been found to contribute to prediction performance,[51,56,59] they are more challenging to capture accurately. Depending on the outcomes, different social or behavioral measures have been found to be significant in the individual-level prediction articles we reviewed. For instance, individual-level income, housing, employment, and education have been found to contribute to the prediction of 30-day readmissions[23]; housing stability, drug use, and high-risk sexual activities contributed to predictive performance of HIV risk assessment[59]; age, substance use, and mental disorders are among the factors that contributed to prediction of suicide attempts[60,61]; and self-perceived health status was a strong predictor of hospitalization. There are no common measures across these articles that can be recommended as a minimum set of measures to capture and record in the EHR. Further, studies have confirmed that the limited set of SDoH information documented in EHRs (eg, race and ethnicity) is challenged with missing data and other quality issues.[67,68] Additionally, individual-level determinants can change rapidly, particularly if patients are successfully referred for appropriate services. The significant gaps in needed electronic health information exchange can hamper the effective collection and use of the ever-changing SDoH information.[69]

Next, the input of such SDoH information into EHRs is limited to the domain of medical providers.[70,71] It is equally important to engage patients in dialogue about their social needs and encourage self-reporting so that providers can ensure that their referrals align with patient priorities and are delivered in an accessible manner. Another key challenge is a lack of consensus on standards for capturing or representing SDoH in EHRs.[70] Patient data is siloed in different systems and technology components of the EHRs and must be shared in new ways to enable the effective crosswalking of SDoH data.

Finally, SDoH-EHR integration for predicting risk of adverse events and identifying early intervention opportunities for patients require processes for downstream planning and tools for actionable decisions by providers, particularly if social risk factors are identified for subpopulations, such as homelessness and food insecurity.[72] Additionally, workforce training, capacity planning, community resource identification, and easy allocation of such resources at the point of care and similar efforts are necessary for effective and efficient use of the analytic insights.[73,74]

Current efforts and screening tools for SDoH-EHR integration

There are federal, state, and local efforts that contribute to the integration of SDoH in EHRs, particularly the individual-level determinants. In 2014, the National Academy of Medicine recommended 11 social and behavioral domains to use for data collection in EHRs.[75,76] However, consensus has not been reached on which SDoH measures can or should be captured in EHRs.[70] Various

Table 4. Comparison of determinants of health in the literature versus the current screening tools

Domains	Dimensions	PRAPARE	Accountable Health Communities Screening Tool	Health Leads Screening Tool	Upstream Risks Screening Tool
Economic stability	Income	•			
	Financial resource	•	•	•	•
	Employment	•	•		
	Clothing[a]	•			
	Utilities (phone, gas, electric)[a]	•	•	•	
	Child care[a]	•		•	
Neighborhood and built environment	Transportation	•	•		•
	Neighborhood	•			•
	Living arrangements	•	•	•	•
	Food access	•	•	•	•
	Environmental conditions[b]				
Health and health care	Insurance status	•			
	Behavioral health (diet, physical activity, tobacco usage, etc.)		•	•	•
	Mental health (stress, depression, etc.)	•	•	•	•
	Need for assistance		•	•	
	Disabilities		•		
	Access to care[b]				
Education	Education	•			•
	Language	•	•	•	
Social and community context	Race/ethnicity	•			
	Social connections	•	•	•	•
	Interpersonal relationship	•	•		•
	Incarceration history	•			
	Migrant/seasonal farmworker/ immigration	•			•
	Veteran status	•			
	Refugee status[a]	•			
	Marital status[b]				

PRAPARE: Protocol for Responding to and Assessing Patients' Assets, Risks, and Experiences.
[a]Appeared only in the screening tools.
[b]Appeared only in the reviewed articles.

patient-facing tools related to the SDoH have since emerged, aiming to allow patients to document their own socioeconomic needs and thus improve the validity and relevance of the social information collected.

Most of these screening tools involve either screening checklists or surveys that are meant to be filled out by patients on their own or completed through a facilitated interview with a clinical staff member. The specific SDoH items included in these tools vary from one to another. To inform efforts to create national standards for representing SDoH information in EHRs, we compared the SDoH measures reported in the literature versus those included in the screening tools used in current practice (Table 4).

We focus on the 4 main SDoH screening tools developed in the United States to help identify SDoH in a primary care setting: (1) the Protocol for Responding to and Assessing Patients' Assets, Risks, and Experiences (PRAPARE) tool by the National Association of Community Health Centers, (2) the Accountable Health Communities Screening Tool, (3) the Health Leads Screening Tool, and (4) HealthBegins Upstream Risks Screening Tool. We categorize the SDoH measures into the 5 key domains outlined by Healthy People 2020. While most of the measures in Table 4 appeared both in the literature and at least 1 of the screening tools, some measures appeared only in either the reviewed articles or the screening tools. The measures that appeared in the literature but not in the screening

tools are related to environmental conditions, access or proximity to healthcare providers, and marital status. Besides the measures of refugee status, the measures screened in practice but not yet evaluated in the literature are mostly in the domains of economic stability (eg, clothing, utilities, and child care).

While all the screening tools cover the 5 domains outlined in Healthy People 2020, they differ in the specific measures they use to screen and collect social and behavior factors within each domain. PRAPARE has the most extensive list of measures in the domains of economic stability, neighborhood and built environment, education, and social and community context. In the domain of health and health care, PRAPARE focuses on insurance status measures while the other screening tools focus on lifestyle (eg, physical activity and dietary pattern), mental health (eg, depression), and need for assistance.

Growing evidence of impact

Although integrating community-based determinants have shown limited impact thus far on improving the performance of risk prediction, area-based SDoH can be used for monitoring disparities.[77] They can also be used to develop population-level indicators that describe the health and quality of life of a geographic community, which provide an opportunity to track and enhance population health on a regional or national level.[22] In contrast to studies with

area-level SDoH data, recent studies that incorporated individual-level SDoH data have all reported significantly improved prediction performance, growing the evidence base with large number of study participants.

In addition to addressing SDoH data collection issues, there is insufficient evidence that social or behavioral risk factors can be effectively addressed through referrals or other action tools. Stronger evidence is needed to demonstrate that data related to SDoH can give a more complete understanding of population risk and improve prediction models. High-quality evidence is also needed to demonstrate that interventions targeting specific SDoH domains, such as referrals to community services, will lead to better clinical outcomes as they help address patients' social needs. Currently, evaluation criteria for referral programs have focused mostly on process measures.[78,79] Yet, most rewards in the era of value-based care are based on improving clinical outcomes and reducing expenditures. More rigorous research with internal validity are needed to focus on the evaluation of both care delivery process and outcomes so that the effectiveness of interventions can be better understood. Finally, there is a need for a greater awareness of the conflation of social (or behavioral) risks with social (or behavioral) determinants. This review suggests that researchers should clarify these key terms and the concepts underlying them in future studies, which could advance policies and practices related to SDoH.

There are limitations to this review. First, although we searched for articles across 5 large databases, we only reported our findings from the published literature and therefore may have failed to capture unpublished studies that might also contain relevant content. Second, owing to the heterogeneity among included studies (eg, different conditions and outcomes studied, various sources and levels of SDoH data elements considered, study designs with or without interventions), it was not possible to systematically apply a quality assessment tool to these studies. Therefore, we included all studies due to their potential to add valuable insight in assessing SDoH's impact.

CONCLUSION

In summary, this systematic review sheds light on the current status of the literature on the integration of SDoH into EHRs, and particularly on the impact of this integration on the risk assessment goals of studies. Our findings support the current policy efforts to establish national standards for representing data related to social and behavioral determinants of health and create tools to incorporate both community- and individual-level determinants into EHRs. It is also important to incentivize the collection of SDoH data through financial or quality measures. Finally, more studies are needed to expand the body of research that measures the impact of SDoH interventions on healthcare outcomes, costs, and population health management, particularly delineating the impact of social and behavioral risk factors.

AUTHOR CONTRIBUTIONS

MC and RP conceived the idea for this study, and MC, RP, and XT designed the study. MC and XT conducted the analysis and drafted the manuscript with extensive inputs from RP. MC, RP, and XT interpreted the results and revised the manuscript. All authors read and approved the final manuscript.

SUPPLEMENTARY MATERIAL

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CONFLICT OF INTEREST STATEMENT

None declared.

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