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Perspective

Social determinants of health in mental health care and research: a case for greater inclusion

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ABSTRACT

Social determinants of health (SDOH) are known to influence mental health outcomes, which are independent risk factors for poor health status and physical illness. Currently, however, existing SDOH data collection methods are ad hoc and inadequate, and SDOH data are not systematically included in clinical research or used to inform patient care. Social contextual data are rarely captured prospectively in a structured and comprehensive manner, leaving large knowledge gaps. Extraction methods are now being developed to facilitate the collection, standardization, and integration of SDOH data into electronic health records. If successful, these efforts may have implications for health equity, such as reducing disparities in access and outcomes. Broader use of surveys, natural language processing, and machine learning methods to harness SDOH may help researchers and clinical teams reduce barriers to mental health care.

INTRODUCTION

Research has consistently demonstrated that lower socioeconomic status (SES) has a strong association with poor overall health and prevalence of many chronic diseases including cardiovascular disease, hypertension, diabetes, and depression.[1–6] The robust association, within and across populations of different countries, is referred to as the "social gradient of health."[7] The gradient is often thought of as linking SES to physical health, but a growing literature suggests its association with mental health issues is particularly important for at least 2 central reasons. First, mental illness is an independent risk factor for worse overall health status and higher rates of physical illness and premature death.[8–12] The social determinants of health (SDOH) have wide-ranging and often unappreciated effects on the overall well-being of individuals and communities. Second, the link between SES and mental health can have large, long-lasting, often generational health effects. For example, adverse childhood experiences, which have an inverse dose-dependent relationship with SES,

can lead to significant developmental disruptions; these are often expressed insidiously through higher prevalence of mental and physical disease in adulthood decades later.[13,14]

Better mental health equity is unlikely without a deeper understanding and targeting of the causal factors related to social determinants of health (SDOH). The importance of income, housing security, education, unemployment, child abuse and neglect, neighborhood conditions, and social support have repeatedly been demonstrated to influence mental health outcomes.[7,15–17] But in clinical practice, these data are often collected in an ad hoc, incomplete manner—if at all—and thus have limited actionable utility in research and care delivery endeavors.

Currently, diverse streams of SDOH data are collected for ad hoc reasons by various stakeholders, including patients, practitioners, researchers, advocacy groups, government agencies, and other public-private entities.[18,19] Data are rarely standardized, often come from unvalidated instruments and questionnaires, and

typically facilitate community-level analyses over individual-level investigation.[20] Their integration into electronic health records (EHRs), and by extension, research and clinical care, is not yet standard practice.[21] But systematically capturing, structuring, and using this data holds the potential to create a new "data asset" in health systems design, clinical care, and research. In this article we highlight current challenges for collecting SDOH data, and provide an overview of possible paths forward, which may help reduce mental health disparities.

DATA COLLECTION AND STANDARDIZATION

Currently, collecting patient-level SDOH data requires documentation by health care providers (eg, in an encounter note in the EHR), self-reported patient questionnaires (paper or electronic), or prospective data collection by researchers for a particular study. Beyond basic demographic information, home address, and history of smoking or substance use, key SDOH measures are not routinely collected by clinicians and health systems despite demonstrated association and causal impact on health outcomes (Figure 1).[22,23] Relevant factors not generally collected include food and housing insecurity, employment barriers, past exposures to abuse (verbal, physical, and sexual), residence in social environments that perpetuate trauma risk, and estimates of social isolation. In the rare cases that such data are collected, care providers often do not use validated instruments raising concerns about data interpretation and secondary use.[24] As a result, individual-level SDOH data collection typically exists in many different formats through various modalities of collection and without a robust underlying framework that could facilitate clinical care, research, and population health management.

Some efforts are being made to address this shortcoming. For example, the PRAPARE tool (Protocol for Responding to and Assessing Patients' Assets, Risk, and Experiences) aims to standardize data collection on several actionable core domains of social determinants such as housing stability, income, and social integration and support.[25] Domains were prioritized for screenings in community health centers, yet the tool has been adapted for use by other institutions in several US regions.[26,27] The availability of PRAPARE and other similar tools, such as HealthBegins and WellRx, are necessary first steps, but they have yet to be implemented broadly across EHR systems or integrated into clinical workflows in facilities caring for patients with mental health disorders (such as primary care settings, specialty and mental health clinics, and free-standing acute mental health facilities).[28–30] More widespread adoption would increase the rate at which such tools are validated across dimensions (ie, internal and external) and improve data collection efforts and our understanding of the health contributions of specific social risk factors.

Some progress can be made by supplementing existing tools. Whereas many of the existing survey tools capture data across a range of social needs, domain-specific question sets should be created and incorporated to supplement such tools and to target distal factors affecting mental health. These factors may include life satisfaction, life meaning and purpose, and beneficial and adverse events in the home or community that impact community stakeholders and neighborhood perception.[31] Additional questions for patients already receiving mental health care could cover structural and attitudinal barriers to treatment, time until treatment is sought, and online resources used for answers or guidance (ie, forums, social media, non-/academic sites).[32] By routinely collecting these data, we can start to address knowledge gaps around how social factors influence mental health outcomes and design care models to address them.

In addition to new prospective SDOH data collection methods, natural language processing (NLP) and advanced machine learning (ML) algorithms can be leveraged to mine existing sources to extract existing data. In many cases, at least some information about a
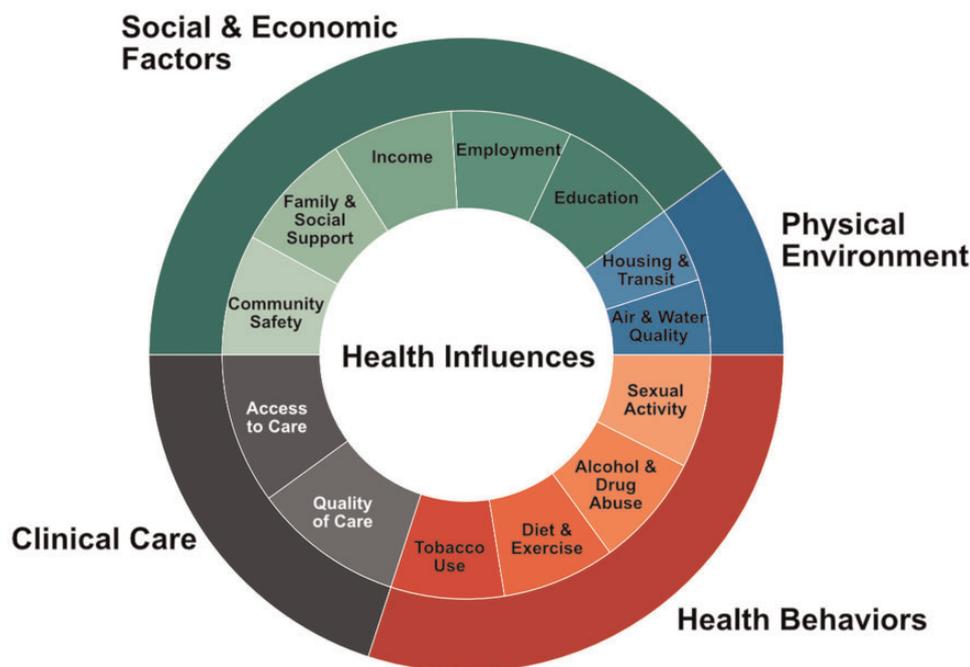

Figure 1. Health influences. Figure 1 has been adapted from County Health Rankings model © 2014 University of Wisconsin-Madison Public Health Institute. http://www.countyhealthrankings.org/what-is-health. The size of each section in the outer loop is associated with estimated influence. Inner loop is split evenly among groups.

patient's social situation is recorded by clinicians in EHR notes. Current work at the intersection of social media and health has also shown that some people may also choose to discuss health-related information and behaviors online through social media channels. NLP, ML and other semantic methodologies (ie, abstracting meaningful data through contextualized processing) are currently being developed to extract race and ethnicity, suicidal ideation and attempts, and problem opioid use from EHR clinical notes and social media data.[33–37] These methods could be extended to extract individual-level concepts such as emotional well-being, financial stability, and other social factors associated with mental health.[38,39] Although these extraction methods may not be as comprehensive as rigorous, prospective data collection tools–and require significant effort to develop–they are able to generate "new" structured data from unstructured sources and potentially improve secondary use of relevant social and health information.

The integration of advanced analytical tools that incorporate SDOH within EHRs raises the issue of interoperability with internal and external systems as a key challenge. EHRs typically lack robust data interoperability and information exchange capabilities and suffer from information redundancy due to data silos. As the amount of SDOH data increases, so too will the work needed to track concept variations, account for duplicates, and maintain parsimonious data models. By adopting standardized health care data standards and vocabularies, such as LOINC (Logical Observation Identifiers Names and Codes) and SNOMED, to describe and classify SDOH concepts, health systems can reduce superfluous, nonstandardized data and better incorporate these concepts into clinical care and decision-support systems.[40,41] Clinical research, community health reporting, and other forms of secondary data uses will benefit from a more unified and uniform representation of data. Whereas there remains the possibility of data multiplicity and variability even with standardized terminologies, health systems can take important steps toward increased data efficiency and interoperability by adopting such data standards.

IMPLICATIONS FOR HEALTH EQUITY

Better collection of SDOH data offers clinicians and health systems the opportunity to identify social correlates of health outcomes that may be missed by routine clinical data elements. Given the broad and profound impact social determinants have on mental and physical health outcomes, it may not be enough to collect narrowly defined social factors like gender, education, poverty, and disability.[42] Further efforts should also aim to capture structural and contextual factors strongly associated with health inequity such as housing security, unemployment, child abuse/neglect, neighborhood conditions, and social support.[43–45]

A risk of many informatics-based interventions is that they may exacerbate inequities by disproportionately benefiting higher SES individuals through better access, adoption, adherence, and effectiveness measures.[46] Patients struggling with mental health disorders may be particularly at risk given the continued stigma around mental illness in many communities.[47–50]

To minimize potential bias, SDOH data should be collected from both traditional (ie, clinical encounters) and non-traditional sources (ie, social media, forums, wearables, mobile apps, and chatbots). NLP, ML and semantically-enhanced methodologies can be applied to social media platforms to augment community-level health surveillance and thus "listen" to individuals who may not be seeking care, but who nonetheless publicly share details related to

depression, suicidal ideation/attempts, or other mental health concerns.[51,52] Relevant signals gleaned from social media can then be used to assess the risk factors of a particular community without invading the privacy of any 1 individual. These data streams can be mined in parallel with active and passive collection of individual-level social data to explore novel relationships through applied ML techniques. ML, in turn, may become hypothesis-generating for further investigations on the impacts of SDOH and potential interventions.

Bridging the knowledge gap is an attainable goal and may allow for carefully designed interventions and policies that increase access, reduce attrition, and improve effectiveness.[53–58] Having access to a more robust set of patient social variables will also allow investigators to 1) perform more sophisticated sampling and recruitment methods, 2) report relevant SES, language, neighborhood, and demographic information; and 3) conduct subgroup analyses with greater accuracy by stratifying across multiple social statuses.[59,60] Research can also take a step further from drawing simple associations by testing increased patient empowerments as well as interventions across groups to determine which interventions are most effective and for whom.[61–63]

CONCLUSION

Despite known associations between social determinants and mental illness, SDOH data are rarely captured in a structured and comprehensive manner by researchers, clinicians, and health systems. In response to increased interest in SDOH data, several collection tools and extraction methods are being developed to facilitate capture of this data and subsequent integration into EHRs. These include survey-based, NLP, and ML methods to collect and characterize attitudinal, structural, and social barriers to care. Incorporation of these data carry the potential to improve care but also to perpetuate or exacerbate existing health disparities if precautions are not taken. But if properly used, better data collection and analysis may allow for the development of new strategies to direct individual patients to appropriate community services, target care toward population-level needs, and reduce barriers to mental health care through informed policy-level decisions.

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CONTRIBUTORS

JJD, SB, JP, and AS crafted the viewpoint and concept design. JJD, SB, DK, JP, and AS drafted the viewpoint. JJD, SB, DK, JP, AS and provided critical revision of the viewpoint for important intellectual content. JP obtained funding. All authors read and approved the final version of the viewpoint.

CONFLICT OF INTEREST STATEMENT

None declared.

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