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Research and Applications

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Patient and clinician acceptability of automated extraction of social drivers of health from clinical notes in primary care

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Abstract

Objective: Artificial Intelligence (AI)-based approaches for extracting Social Drivers of Health (SDoH) from clinical notes offer healthcare systems an efficient way to identify patients' social needs, yet we know little about the acceptability of this approach to patients and clinicians. We investigated patient and clinician acceptability through interviews.

Materials and Methods: We interviewed primary care patients experiencing social needs ($n = 19$) and clinicians ($n = 14$) about their acceptability of "SDoH autosuggest," an AI-based approach for extracting SDoH from clinical notes. We presented storyboards depicting the approach and asked participants to rate their acceptability and discuss their rationale.

Results: Participants rated SDoH autosuggest moderately acceptable (mean = 3.9/5 patients; mean = 3.6/5 clinicians). Patients' ratings varied across domains, with substance use rated most and employment rated least acceptable. Both groups raised concern about information integrity, actionability, impact on clinical interactions and relationships, and privacy. In addition, patients raised concern about transparency, autonomy, and potential harm, whereas clinicians raised concern about usability.

Discussion: Despite reporting moderate acceptability of the envisioned approach, patients and clinicians expressed multiple concerns about AI systems that extract SDoH. Participants emphasized the need for high-quality data, non-intrusive presentation methods, and clear communication strategies regarding sensitive social needs. Findings underscore the importance of engaging patients and clinicians to mitigate unintended consequences when integrating AI approaches into care.

Conclusion: Although AI approaches like SDoH autosuggest hold promise for efficiently identifying SDoH from clinical notes, they must also account for concerns of patients and clinicians to ensure these systems are acceptable and do not undermine trust.

Key words: social determinants of health; electronic health records; artificial intelligence; interview; stakeholder participation.

Background and significance

Despite being historically regarded as non-medical, social drivers of health (SDoH)[1] influence health outcomes and equity.[1–3] The Center for Medicare & Medicaid Services (CMS) has identified standardized SDoH collection, report, and analysis as a priority for health equity.[4] Starting in 2024, CMS began requiring healthcare organizations to report on SDoH screening under the Hospital Inpatient Prospective Payment System final rule.[5] The Office of the National Coordinator for Health Information Technology also emphasized using standardized SDoH elements in clinical decision support tools to improve health equity and outcomes.[6] Traditional SDoH screening, conducted via patient questionnaires or clinician-led interviews, plays a key role in identifying patients' social needs.[7,8] However, significant barriers hinder the effective integration of SDoH screening into clinical workflow, including lack of screening technology, challenges related to training and availability of resources to support screening, resistance from clinicians and staff, and reluctance from patients.[9,10] As national SDoH requirements grow, healthcare systems need methods to capture SDoH data more efficiently in electronic health records (EHRs) and clinical workflow.[7,11] Beyond capturing SDoH, presenting SDoH information in the EHR to clinicians has been shown to enhance clinical decision-making and improve communication.[12] Artificial intelligence (AI) systems that leverage

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natural language processing (NLP) present a promising solution to automate the extraction and presentation of SDoH information from unstructured clinical notes. However, we know little about the perspective of patients and clinicians about this approach. In this study, we address this gap through the use of a design concept of an AI-based approach that extracts SDoH from clinical notes and presents that data to clinicians—an envisioned approach we call "SDoH autosuggest." Such AI-based systems have the potential to augment active SDoH screening by providing additional context from historical clinical notes—but will clinicians and patients welcome the use of such systems?

The application of AI to extract information from clinical notes[13] has been studied in a wide range of use-cases, such as recognizing medical entities,[14,15] acquiring sleep information,[16] and identifying SDoH from clinical notes.[17–22] Previous research has also demonstrate high accuracy of identifying SDoH using large language models (LLMs).[18,19,23,24] For instance, a fine-tuned LLM was able to identify 93.8% of patients with SDoH.[23] Another study reported an averaged F1 scores, a metric that balances precision and recall to measure a model's accuracy in identifying relevance instances, over 0.9 using LLM.[19] AI-based systems, by culling previously documented social needs in patient narratives, could reduce barriers to documenting SDoH,[25] could reduce the fragmented view of patients and scattered SDoH data in EHRs, and potentially improve outcomes and reduced costs.[26] EHR tools, such as EPIC's "wheel," facilitate the documentation and presentation of social risks but rely on manual data entry or patient self-reporting. These methods face limitations such as time constraints and reliance on clinicians' initiative.[12] Studies have shown limited clinician engagement with structured SDoH data.[27] AI systems that automatically suggest SDoH to clinicians have the potential to prompt conversations based on a patient's SDoH history documented in clinical notes. These systems can complement existing social needs screening tools, addressing gaps in clinical workflows, and have the potential to help healthcare organizations meet CMS reporting requirements,[5] fostering more informed patient interactions[12] and improving clinical care by taking more of a patient's life circumstances into consideration.[28]

Despite the policy incentives, potential benefits, and technical feasibility, the design and implementation of AI systems for SDoH require careful consideration to prevent unintended consequences that could negatively impact patient care, patient-provider relationships, and patient trust in healthcare systems.[29] Previous studies discuss the impact of AI on patient privacy and data sharing,[30] decision support,[31,32] and healthcare.[33,34] Researchers have examined social impacts of AI systems, such as the ethics of NLP from a data and model standpoint.[35] Use of LLMs for SDoH raises new challenges for equitable AI, including bias in algorithms and privacy concerns.[24] For instance, clinical notes may contain implicit biases, such as stigmatizing language,[36] which AI models can inadvertently learn and perpetuate, and adversely affect model performance.[37] Engaging people from groups who may be impacted by the technology is critical to identifying concerns and potential unintended consequences.[38]

To date, research on the perspectives of patients and clinicians on AI systems for SDoH remains limited, despite the potential for considerable concerns.[39–43] Challenges surface when integrating SDoH into healthcare, including time and resources required, inadequate training, lack of actionable information, and uncertainties about how the information should be used.[44–46] Clinicians and staff also face organizational and administrative hurdles when incorporating SDoH screening and referral into clinical workflows.[47] A systematic review found that while patients understand the reasons for SDoH screening, their opinions on its implementation in EHRs vary.[48] Additionally, a survey revealed that 20% of primary care patients expressed discomfort with the inclusion of social needs information in their EHR, with discomfort increasing proportionally to the number of social needs experienced.[49] These findings warrant further investigation of patient perspectives, particularly those with social needs, in the context of AI systems. Although prior research has examined patient and clinician views on SDoH screening and on use of AI in healthcare separately, we know very little about how acceptable patients and clinicians find AI systems for SDoH in clinical settings.

Objective

The purpose of this study was to investigate the acceptability of an envisioned AI-based approach we call "SDoH autosuggest" (Figure 1). We used SDoH autosuggest as a design concept to probe patients and clinicians about potential benefits and concerns of using AI to extract and present SDoH in EHRs. We address the following research questions in the context of primary care:

RQ1. How acceptable do patients and clinicians find the SDoH autosuggest approach?
RQ2. What benefits and concerns do patients and clinicians express regarding this approach?

Materials and methods

Study design

We conducted semi-structured interviews in two phases with (1) primary care patients who experience social needs and (2) primary care clinicians to compare their perceptions of the SDoH autosuggest approach. A team of clinical experts and a community advisory board helped design and pilot study procedures,[29] which were reviewed by the Institutional Review Board at the University of Washington (UW) (#STUDY00015691).

Recruitment

Patients

From October 2022 to August 2023, we recruited patients from UW Medicine primary care clinics in Seattle, Washington. Recruitment methods include flyers in clinics that serve a high proportion of patients with social needs and direct outreach by clinic staff. Interested patients completed a screening survey (Supplement S1) for determining eligibility (≥18 years of age, English-speaking, with one or more self-reported social needs[41]) and purposive sampling (digital health care literacy,[50] number of social needs). We recruited a balance of participants with lower (<6) and higher (≥6) digital literacy and with a lower (<3) and higher (≥3) number of social needs. The cutoff for socials needs was chosen empirically. We offered in-person or Zoom interviews.

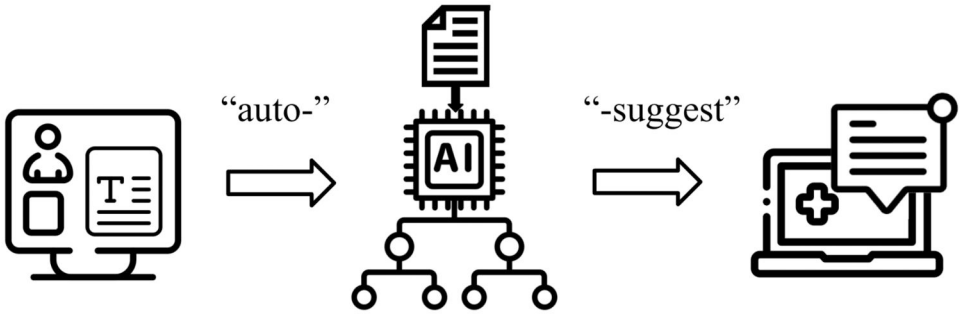

Figure 1. The "SDoH autosuggest" approach is a design concept the envisions an AI-based system that uses NLP to automatically extract SDoH from clinical notes ("auto-") in the EHR and presents this information to healthcare providers for review ("-suggest"). We used this design concept as a probe to investigate patient and provider acceptability and perceived benefits and concerns of future EHR systems that use AI to extract and present SDoH from clinical notes.

Clinicians

From August 2023 to November 2023, three co-authors (BRW, APS, JWK) recruited clinicians from UW Medicine primary care clinics using emails through listservs and professional networks. We employed convenience sampling and conducted interviews via Zoom.

Data collection

Participants completed semi-structured interviews and surveys. Both patient and clinician interviews lasted 45-60 min and were recorded and transcribed for qualitative analysis. We conducted interviews until reaching thematic saturation.

Patients

Interviews collected ratings of acceptability, perceived benefits, and concerns regarding the SDoH autosuggest approach. During interviews, we used storyboards[51] (Supplement S3), which were designed to engage participants in provocative scenarios to test the boundaries of what is and is not acceptable. The storyboards depict four scenarios of how SDoH autosuggest could be implemented in clinical care for four SDoH domains: food security, employment, housing stability, and substance use. We selected the four domains based on varied levels of stigma,[52–55] prevalence in primary care[56,57] and feasibility of NLP extraction from EHRs.[21,22,58,59] For each scenario, we asked participants to share their general impression of the approach, rate their acceptability using the 5-point Likert Scale Acceptability of Intervention Measure (AIM),[60] and provide rationale for their ratings, including any benefits or concerns regarding the approach (Supplement S4). The patient survey included questions on demographics, self-rated health,[61] and healthcare utilization[62] (Supplement S2).

Clinicians

During interviews, clinician participants were shown one storyboard that referenced the same four SDoH domains shown to patients and asked to put themselves in the shoes of the fictitious "health care provider" caring for a new patient (Supplement S6). Clinicians were asked questions similar to patients about their general impressions and to rate the acceptability, feasibility, and appropriateness of the approach using the 5-point Likert Scale AIM, Feasibility of Intervention Measure (FIM), and Intervention Appropriateness Measure (IAM),[60] and describe the rationale for their ratings, including any benefits and concerns (Supplement S7). The clinician survey collected demographics and clinical experience (Supplement S5).

Data analysis

We summarized survey and rating data using descriptive statistics. We performed Friedman Test (X^2) with post-hoc pairwise comparisons using Wilcoxon Signed-Rank Tests (W) with Bonferroni corrections to compare patient AIM ratings among the scenarios, and Mann-Whitney U test (U) to compare AIM ratings between patients and clinicians between various groups: patients versus clinicians, patients with higher versus lower social needs, patients with higher versus lower digital literacy, and clinicians with a higher versus lower proportion of patients with social needs on their panel.

We analyzed interview transcripts in two phrases. During phase 1, inductive content analysis[63] to patient interview transcripts was conducted in parallel with data collection to ensure that thematic saturation was achieved. After the first five interviews, four co-authors (SJX, CS, PW, AH) independently reviewed four transcripts and discussed emerging patterns. Two coders (SJX, CS) then coded these transcripts in ATLAS.ti and developed an initial codebook, which was refined iteratively through coding of five additional transcripts and weekly consensus meetings to evaluate whether thematic saturation had been reached. One coder (SJX) applied the final codebook to all patient interview transcripts.

In the second phase, we used directed content analysis to deductively analyze clinician transcripts. The two coders independently coded half of clinician interview transcripts using the codebook developed in phase 1, discussing and incorporating extensions to capture new emerging codes. Five co-authors (SJX, CS, ALH, PW, RL) participated in weekly meetings to achieve consensus on these additional codes. The final codebook, capturing both clinician and patient perspectives, was collaboratively refined to delineate themes and subthemes supported by quotes from multiple participants. Finally, one coder (SJX) applied the finalized codebook to all clinician interview transcripts.

Results

Characteristics of participants

Thirty-three participants completed interviews, including 19 patients (P1-P19) and 14 clinicians (C1-C14) (Table 1). Seven patients participated in interviews in-person and 12 participated via Zoom. Patient participants were majority White

Table 1. Participant characteristics.

Characteristics	Patient participants ($n = 19$)	Provider participants ($n = 14$)
Age group *n* (%)		
30-39	3 (15.8%)	—
40-49	5 (26.3%)	—
50-59	10 (52.6%)	—
>60	1 (5.3%)	—
Number of years practicing clinically (*mean (SD)*, range)	—	11.2 (7.5), 2-24
Gender *n* (%)		
Woman	4 (21.1%)	9 (64.3%)
Man	15 (78.9%)	5 (35.7%)
Race *n* (%)		
American Indian or Alaska Native	1 (5.3%)	0 (0%)
Asian	2 (10.5%)	8 (57.1%)
Black/African American	3 (15.8%)	1 (5.3%)
White	12 (63.2%)	5 (35.8%)
Some other race	1 (5.3%)	0 (0%)
Ethnicity *n* (%)		
Hispanic/Latino	3 (15.8%)	0 (0%)
Not Hispanic/Latino	16 (84.2%)	14 (100%)
Education *n* (%)		
High school or GED	7 (36.8%)	—
Some college	6 (31.6%)	—
Associate's degree	5 (26.3%)	—
Bachelor's degree	1 (5.3%)	—
Health insurance *n* (%)		
Medicaid	12 (63.2%)	—
Medicare	3 (15.8%)	—
Unknown	4 (21.1%)	—
Clinical role		
Physician	—	12 (85.8%)
Physician Assistant	—	1 (7.1%)
Advanced Registered Nurse Practitioner/Doctor of Nursing Practice	—	1 (7.1%)
Clinical setting		
Academic medical center	—	9 (64.3%)
Community clinic	—	3 (21.4%)
Both	—	2 (14.3%)
Frequency of health care visits in the past 6 months (*mean (SD)*, *range)*	4.7 (3.9), 1-15	—
Digital health care literacy score (mean, SD, range)	6.7 (4.6), 0-12	—
Lower digital literacy (<6)	7 (37%)	
Higher digital literacy (≥6)	12 (63%)	
Number of social needs (*Mean (SD)*, range*)*	4.3 (2.5), 1-8	—
Lower number of social needs (<3)	8 (42%)	—
Higher number of social needs (≥3)	11 (58%)	—
Panel size (number of patients cared for each week) (*mean (SD)*, range)	—	43 (18.6), 10-70
Proportion of patients with social needs (*mean (SD)*, *range*)	—	67.1% (30.7%), 15%-100%
Lower proportion of patients with social needs (< 50%)	—	7 (50.0%)
Higher proportion of patients with social needs (≥50%)	—	7 (50.0%)
Level of comfort with using EHR (*mean (SD)*, *range*)	—	8.8 (0.8), 8-10

non-Hispanic men, publicly insured, diverse in age and digital literacy, and over half experienced more than three social needs. Clinician participants were majority White non-Hispanic women physicians with more than 10 years of clinical experience. They practiced in ten different primary care clinics, had diverse panel sizes, and reported a high level of comfort with using EHR.

RQ1. How acceptable do patients and clinicians find the SDoH autosuggest approach?

On average across the 4 scenarios, patient participants rated SDoH autosuggest as moderately acceptable (mean = 3.9, SD = 0.7, range = 2.3-5). Their acceptability ratings differed significantly by SDoH domain ($\chi^2(3) = 13.8$, $P < .01$) with substance use rated most acceptable, followed by food security, housing stability, and employment (Figure 2). Acceptability ratings for employment were significantly lower than substance use ($W = 62$, $P = .03$) and food security ($W = 36$, $P = .04$). When asked about the reason behind the varying acceptability across SDoH domains, the perceived relevance of each domain to healthcare was viewed as a priority. Employment was perceived as least relevant while substance use was perceived as most relevant. Ratings did not differ between participants with high and low social needs or high and low digital literacy.

On average, clinician participants rated SDoH autosuggest slightly less acceptable than patient participants (mean = 3.6, SD = 1.0, range = 2-5) and somewhat feasible (mean = 3.6, SD = 0.6, range = 2.8-4.5) and appropriate (mean = 3.4, SD = 1.1, range = 2-5). Although clinician participants' acceptability ratings were lower than patient participants' (averaged across four scenarios), this difference was not significant (Figure 3). Clinician participants reported that they

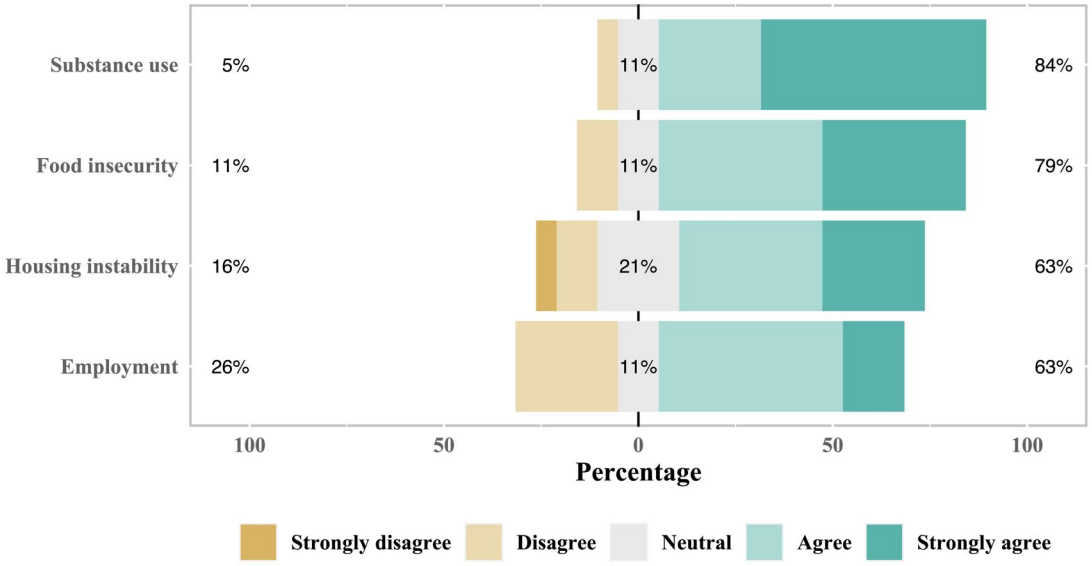

Figure 2. Distribution of patient participants' acceptability ratings across the four social need scenarios.

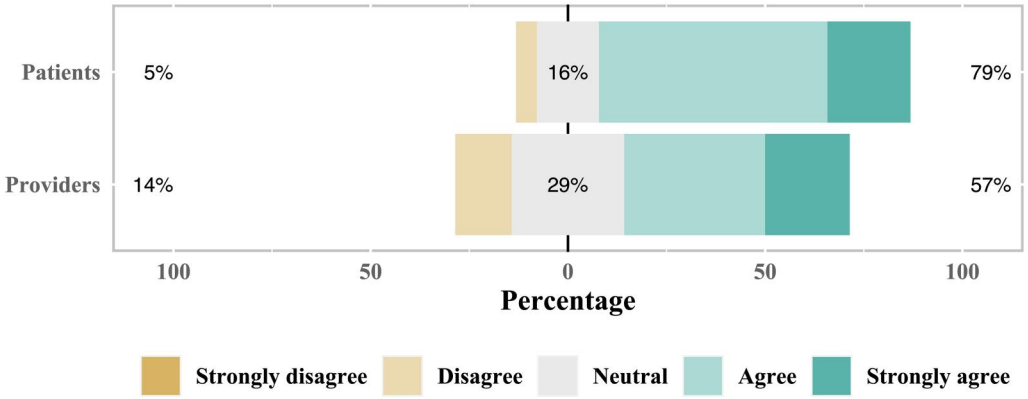

Figure 3. Distribution of acceptability ratings of patient participants and clinician participants.

would not rate acceptability, feasibility, or appropriateness of the approach differently across the four SDoH domains. Ratings did not differ between participants who had a higher and lower proportion of patients with social needs on their panel.

RQ2. What benefits and concerns do patients and clinicians express regarding the SDoH autosuggest approach?

We identified five themes from the interviews with patients and clinicians: (1) Perceived benefits, and concerns about (2) information integrity, (3) usability and actionability, (4) impact on clinical interactions and relationships, and (5) ethics (Table 2). Although participants rated SDoH autosuggest somewhat highly, potential benefits and concerns emerged in the rationale they provided for those ratings. Representative quotes for each theme mentioned in the text are included in Supplement Table (Supplement S8). The quotes are labeled with participant numbers (eg, P9, C4), which correspond to the participants who provided these responses. These numbers are used solely for referencing and do not indicate that specific subthemes are ascribed to individual participants.

Theme 1. Perceived benefits

Allows for more informed care

Patients emphasized the benefit of providers being well-informed about their SDoH, noting that they would approve the SDoH autosuggest approach if the extracted information could help improve their healthcare (P9). A few patients highlighted the importance of surfacing substance use information to clinicians (P15). Some patients appreciated that SDoH autosuggest could provide clinicians continuity of patients' social histories without requiring them to repeatedly describe and relive experiences (P12). Clinicians recognized the benefit of making fewer assumptions about whom to ask or not ask about social needs (C1). A few clinicians valued the system's ability to remind and prompt considerations of SDoH (C7), fostering a more holistic approach to care (C2).

Enables clinicians to efficiently review charts

Clinicians appreciated how SDoH autosuggest could efficiently synthesize social needs from clinical notes, reducing the risk of overlooking crucial information that can impact health outcomes (C3). Clinicians also recognized the potential benefit of leveraging previously collected information to save time and increase thoroughness when learning about patients' dynamic lives (C4).

Table 2. Themes and subthemes expressed by patient and clinician participants.

Theme	Subtheme	Expressed by	
		Patients	Clinicians
Perceived benefits	Allows for more informed care	✓	✓
	Enables clinicians to efficiently review charts		✓
	Facilitates data use beyond clinical care		✓
Concerns about information integrity	Derived from retrospective data	✓	✓
	Based on oversimplified algorithms	✓	✓
Concerns about usability and actionability	Adds more to already busy patient visits		✓
	Forces conversations about issues without actionable help	✓	✓
	Presents SDoH information in hard-to-find and disruptive ways		✓
Concerns about impact on clinical interactions and relationships	Enables clinician overreliance on the extracted information	✓	✓
	Leads patients to question the relevance of some SDoH domains	✓	✓
	Induces stigma toward patients	✓	✓
	Introduces bias into encounters		✓
Concerns about ethics	Surfaces information viewed as private	✓	✓
	Lacks transparency and autonomy	✓	
	Creates susceptibility for patient harm	✓	

Facilitates data use beyond clinical care

Some clinicians also noted benefits beyond the use for clinical care, including being useful for billing (C11) and supporting population health research (C14).

Theme 2. Concerns about information integrity

Derived from retrospective data

Both patients and clinicians raised concerns about the accuracy of extracted SDoH information documented in clinical notes. Patients emphasized the concern about inaccurate information documented by clinicians in the source clinical notes, and the SDoH autosuggest approach then posed the risks of perpetuating misinformation (P5, P8). This point was echoed by some clinicians (C5). The majority of clinicians also emphasized the false sense of objectivity while using potentially incomplete or outdated data. If the patient was never asked about their social needs (C1) or had not previously received care in the healthcare organization (C4), the relevant SDoH information might not be accessible, leading to clinicians potentially missing patients' social needs. Even if social needs were documented in clinical notes, SDoH information from years ago may be outdated and no longer reflect a patient's current situation (C3). If clinicians regarded the extracted SDoH as "factual" without further verification, it could lead to misinterpretations and misguided decisions.

Based on oversimplified algorithms

Even when SDoH data is accurate, participants expressed concerns about the design of algorithms used to extract this information. Both groups felt algorithms could simplify patients' complex social needs into a binary "flag" (P6), "box or category" (P7), or "label" (C8) that lacks sufficient context for clinicians to understand nuance in patients' underlying situations (P6). Moreover, clinicians questioned whether an algorithm could precisely capture all relevant social needs documented in the EHR (C4).

Theme 3. Concerns about usability and actionability

Adds more to already busy patient visits

Clinicians worried that SDoH autosuggest could further reduce their limited time interacting with patients (C9), adding to the existing burden of collecting extensive information during visits (C12).

Forces conversations without actionable help

Patients expressed concern that SDoH autosuggest might prompt more frequent conversations about social needs without providing actionable resources, leading to frustration (P16, P12). Clinicians also expressed concern about the emotional toll of more frequent reminders about patients' social needs they are unable to adequately address, contributing to burnout (C9). Notably, there was high heterogeneity in clinicians' SDoH workflows across clinics. Some clinics had more resources dedicated to screening and referral, while others shared a single case manager or social worker among multiple clinics. Clinicians in low-resource settings expressed uncertainty about having the means to address identified social needs, even if SDoH autosuggest could help in identifying them.

Presents SDoH information in hard-to-find and disruptive ways

All clinicians expressed concern regarding where the extracted SDoH information would be presented and how they would interact with it. Some clinicians worried that the extracted SDoH might still be hard to locate, leading to resistance in adopting the approach (C4). Others worried that the extracted SDoH could be presented in a disruptive way, such as alerts that contribute to fatigue (C6). Clinicians preferred non-intrusive methods, allowing them to seek information passively without it being forced upon them (C10).

Theme 4. Concerns about the impact on clinical interactions and relationships

Enables clinician overreliance on the extracted information

Both clinicians and patients were concerned that clinicians might overly rely on the extracted SDoH information. Some patients worried that this reliance could lead clinicians to skip asking them about their social needs, potentially missing important details (P11) or the full context of their situation (P15). Some patients worried that one clinician's biased conclusions could perpetuate in the system, influencing future

clinicians' decisions (P18). Clinicians also expressed apprehension about accepting auto-suggested SDoH information as fact without verification (C6) and no longer assessing patients' social needs on their own (C4).

Leads patients to question the relevance of some SDoH domains

Some clinicians expressed concern, based on their experience, that patients might question the relevance of certain SDoH domains to healthcare visits, which could "annoy" (C5) or provoke (C14) some patients and negatively affect the patient-provider relationship. This concern was echoed by patients, with some expressed strong disapproval for specific SDoH domains they perceived as irrelevant to healthcare, particularly employment information (P4).

Induces stigma toward patients

Most patients expressed concerns about feeling embarrassment, uncomfortable, vulnerability, or judged if extracted information was shown to clinicians they hadn't previously seen (P6, P4). Some clinicians also recognized the potential for stigma associated with SDOH autosuggest, which could lead patients to feel "judged" (C1). Clinicians emphasized the importance of building trust and rapport before using extracted SDoH information in clinical care (C11).

Introduces bias into encounters

A few clinicians were concerned that SDoH autosuggest could introduce bias into clinical encounters, as clinicians may have their own stereotypes (C5) and inherent biases (C2). Caring for patients with social needs often requires more time and energy compared to patients without social needs. Seeing the extracted SDoH information in advance could affect a clinician's approach and care decisions (C6).

Theme 5. Concerns about ethics

Surfaces information viewed as private

Some patients expressed strong disapproval of the SDoH autosuggest approach for certain SDoH domains they viewed as private (P8). Even if they shared certain social needs with a trusted clinician, they may still consider that information confidential and not want others who access the EHR to see those "secrets" (P1, P5). When SDoH information patients consider private is surfaced in discussions with new providers, it could result in a loss of trust in clinicians and the healthcare system (P1). Clinicians also shared concerns about "digging up" and perpetuating sensitive SDoH information, which could frustrate patients (C13).

Lacks transparency and autonomy

Patients called for transparency, believing patients should be informed about how their social needs are extracted and surfaced in the EHR. Lack of such transparency was seen to create "problems" (P2). P12 suggested the option for patients to limit access to their SDoH information and not feel forced to share this information.

Creates susceptibility for patient harm

Patients expressed concern that the extracted SDoH data could be misused, potentially affecting their healthcare insurance coverage (P5, P7) or result in discrimination by healthcare facilities, potentially limiting patients' access to care (P3).

Discussion

Through interviews with storyboards depicting an AI-based approach to extract SDoH, we found that patients and clinicians rate acceptability of the approach moderately high yet voice more concerns than perceived benefits. Unlike clinicians, patient acceptability varied by SDoH domain based on perceived relevance to healthcare. Both patients and clinicians raised concerns regarding extracted information integrity, system usability and actionability, impact on clinical interactions and relationships, and ethics. Although most concerns were expressed by both groups, clinicians also raised concerns about system usability and bias. Patients also voiced ethical concerns about transparency, autonomy, and potential future harm.

Compared with prior work that describes concerns related to SDoH screening more generally,[7,9,39] such as screening burden,[64] incorporating screening technology into the clinical workflow,[25] workflow integration,[64] and limited availability of resources for screening and referral,[46] our findings both align with prior work and contribute new insights specific to AI. For example, our findings point to the potential benefit of AI-based approaches in alleviating challenges regarding clinicians' decision-making about whom to screen. Other findings also identify specific risks AI can introduce, such as oversimplified algorithms and missing context. Our findings also align with the perceived burden providers report to social needs screening in general, such as lack of time,[46,65] however, our findings uniquely pointed out the emotional toll for healthcare providers seeing unmet needs of the patients without actionable solutions. Our findings further emphasize the risk of overreliance on AI-based approached that could potentially bypassing direct patient-clinician communication. This aligns with the unintended consequence over trust in AI recommendations identified for AI-driven clinical decision support[31] and calls for greater clinician vigilance.[66] Our findings also strongly resonate with patient concerns regarding fear of judgment, stigma, and potential harm from sharing sensitive social information,[10,67,68] which could be exacerbated by AI-based systems[29] that surface patient narratives that some patients could regard as private. Our findings contribute a deeper understanding of patients' desires for autonomy, transparency, and control over sharing SDoH information. Lastly, although the current study did not evaluate an implemented system, our finding highlighted the potential for usability concerns that could disrupt patient-provider rapport and add burden. Using the 5 Rights of Clinical Decision Support framework,[69] (ie, the right information, to the right person, in the right format, through the right channel, at the right time in the workflow), we discuss the implications of our findings, including considerations for designing AI systems for SDoH.

Many concerns participants raised revolve around presenting the "right information" to users. While prior research demonstrates promising accuracy in SDoH extraction,[18,19,23] concerns raised by our study participants extend beyond extraction accuracy to the comprehensiveness and completeness of the underlying data used for extraction. To enhance comprehensiveness, data used for extraction could integrate multiple data sources, such as patient records across multiple healthcare organizations using Care Everywhere[70] or other novel data integration methods, such as linking with public surveys and environmental data.[11,71] However, the potential

benefit of multi-source integration must be weighed against privacy concerns. To mitigate concerns about algorithms' oversimplification and reliability, AI systems for SDoH could employ strategies such as displaying timestamps and details from the original source sentence, providing an explicit link between the extracted information and its source. Moreover, the AI-extracted information could be presented in familiar EHR interfaces design for SDoH, such as EPIC's "wheel" and related interfaces. Presenting and suggesting extracted structured data to clinicians can introduce pitfalls of considering imperfect structured data as high quality,[72] such as failing to capture the nuances of contexts[73] and creating a false sense of objectivity.[74] Moreover, algorithms trained on biased or incomplete datasets risk could perpetuate disparities in care.[75–77] Addressing this requires not only diverse training data and equity audits[20,75] but also engaging stakeholders during development and testing phases to help identify and mitigate potential sources of bias.[29] The "right information" might also include supplementary information for clinicians, such as suggestions on non-judgmental communication strategies[78] and quick-access links to resources. These design considerations could enhance greater clinician empathy and help them feel more adequately prepared.[44]

AI systems like SDoH autosuggest should also ensure that the extracted information is directed to the "right person." Given clinicians' concerns about limited time and resources to address SDoH, careful consideration is needed for which care team members, such as nurses, case managers, or social workers, have the skills and capacity to take actionable next steps. This design consideration aligns with previous research in which clinicians were confused about their roles and patient navigator responsibilities in a SDoH screening and referral process.[47] AI systems for SDoH should clearly define user roles and present relevant information to care team members based on those roles to streamline care coordination. A one-size-fits-all determination for who will review, update, and act on the extracted information may not account for the heterogeneity of clinic resources we observed, particularly for clinics with limited resources for SDoH workflows.[65] Moreover, patient privacy and stigma remain critical ethical considerations closely related to directing the information to the "right person" and are particularly acute for AI systems for SDoH that deal with sensitive social information.[29] Given that patients viewed some SDoH information as private, enabling restrictions on sharing certain SDoH has merit. As AI becomes more prevalent in healthcare, data sharing and consent will remain critical topics.[30,34] Stigma associated with SDoH data was a recurring theme, with participants expressing fears of judgment or negative labeling. This aligns with broader research showing that individuals experiencing social needs often face stigmatization in clinical encounters,[49] which can deter them from seeking care. The inclusion of SDoH information in EHRs, especially if extracted without patient consent, risks amplifying these issues. To address this, future systems must carefully consider how and whether SDoH information is extracted and presented to EHR users. Non-judgmental language, contextual explanations, and training for clinicians on equitable communication strategies are essential to mitigate stigma. Research is needed to amplify voices of people from vulnerable communities,[79] ensuring that technological design incorporates perspectives from groups likely to be most impacted.

It is crucial to consider the "right time" and "right format" when integrating AI systems for SDoH into clinical workflows in ways that facilitate adoption. Some clinician participants favored non-intrusive information presentation but wish to avoid extensive navigation, which present an opportunity to design AI systems for SDoH with flexibility. As patients emphasized the importance of rapport-building,[44,80,81] systems should also be designed to foster rapport-building conversations, instead of inhibiting them, with the inclusion of contextual details and limiting the use of labels. Furthermore, utilizing the "right channel" could potentially enhance transparency and autonomy.[29] For example, AI systems for SDoH could leverage patient portals to ask patients to review and verify their extracted SDoH information just like reviewing their laboratory test results.[82] However, it is important to recognize that patients with social needs may have limited digital literacy and limited access to technology, such as patient portals.[83]

Our findings suggest several policy implications at both organizational and regulatory levels. At the organizational level, healthcare systems implementing AI-driven SDoH tools should establish clear guidelines and frameworks[84] to mitigate concerns about information integrity, usability, and privacy. Policies should define roles and responsibilities among care team members to ensure that extracted SDoH information leads to actionable interventions rather than unaddressed documentation. Moreover, organizations should allocate resources to support training initiatives that equip clinicians and staff with skills needed to effectively utilize AI-extracted information while recognizing its limitations. Policies should also prioritize community engagement, ensuring that patient voices are heard and reflected in development and implementation decisions, for instance, incorporating mechanisms for patient consent to enhance autonomy and transparency. Engaging patients, particularly those from vulnerable communities, into governance processes can help identify potential risks and support equitable outcomes.[29] At the state and federal level, in addition to standardization of AI-derived SDoH data, agencies could provide comprehensive guidance on ethical use of AI-extracted SDoH information. This includes requirements for bias auditing throughout the AI development lifecycle, safeguards against potential misuse, and governance frameworks that support health equity.[38,77]

Our study has several strengths and limitations. By focusing on patients with social needs, we elicited perspectives of individuals who might be most impacted by AI systems like SDoH autosuggest. Involving a panel of clinical and community champions in the creation of study materials enabled us to effectively recruit and engage participants with varying levels of digital literacy and social needs.[29] However, asking participants to imagine themselves in a theoretical scenario they may not have personally experienced could have impacted results. Future work should further explore views of patients from diverse backgrounds about their experiences with technology facilitated SDoH screening and referral.[85] Another limitation is that our sample included only English-speaking patients. Engaging non-English speaking individuals in future research may reveal unique challenges, such as mistrust of healthcare systems.[86,87] Future research should engage a larger number of patients with diverse backgrounds. While engaging a hard-to-reach patient population with social needs was a strength of this study, some participants

might hold biases about the acceptability of social needs screening that do not translate to other groups. For example, Rogers et al[88] found that patients with recent social needs were over three times as likely to agree that health systems should inquire about and help address social needs. Future research should also explore perspectives of patients without social needs.

Our findings suggest several actionable steps to advance the development and integration of AI systems like SDoH autosuggest. First, there is a clear need for collaborative co-design with diverse stakeholders, including patients, clinicians, healthcare administrators, and others involved in SDoH, to align systems with user needs and clinical workflows. Additionally, future research should explore features and methods that could address concerns and adoption barriers to maximize the impact of AI system for SDoH on care delivery and health outcomes. Key areas to explore include incorporating features such as source linking and timestamps to build trust in extracted information, developing mechanisms for patient to have control over their sensitive SDoH data, and equipping clinicians with tools and resources to interpret SDoH information and facilitate discussion that minimize stigma.[78]

Conclusion

Although AI approaches like SDoH autosuggest hold promise for efficiently identifying patient SDoH from clinical notes, the perspectives of patients and clinicians are critical for informing the design and implementation of systems that are acceptable and mitigate concerns that could otherwise lead to unintended consequences. Study findings highlight the importance of engaging patients and clinicians to surface concerns that could undermine the acceptability, reliability, effectiveness, and mitigate ethical concerns and unintended consequences of these systems. Proactive, human-centered AI will be essential.

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Author contributions

Serena Jinchen Xie, Andrea L. Hartzler, Kevin Lybarger, Angad Preet Singh, and Patrick Wedgeworth contributed to the conception of the study. Serena Jinchen Xie, Andrea L. Hartzler, Kevin Lybarger, Gary Hsieh, Brian R. Wood, Angad Preet Singh, and Herbert C. Duber contributed to the design of the study and study materials. Serena Jinchen Xie, Carolin Spice, Patrick Wedgeworth, Raina Langevin, Brian R. Wood, Jared W. Klein, and Andrea L. Hartzler contributed to the data collection and analysis. Serena Jinchen Xie, Carolin Spice, Patrick Wedgeworth, Raina Langevin, Brian R. Wood, Angad Preet Singh, and Andrea L. Hartzler contributed to the interpretation of the results. Serena Jinchen Xie, Andrea L. Hartzler, Carolin Spice, Patrick Wedgeworth, and Raina Langevin drafted the manuscript. All authors revised the manuscript, approved the final version.

Supplementary material

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

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Conflicts of interest

The authors have no competing interests to declare.

Data availability

The participants and interview data underlying this article cannot be shared publicly for the privacy of individuals that participated in the study.

References

1. Friedman NL, Banegas MP. Toward addressing social determinants of health: a health care system strategy. *Perm J*. 2018;22. https://doi.org/10.7812/TPP/18-095
2. Daniel H, Bornstein SS, Kane GC, et al.; Health and Public Policy Committee of the American College of Physicians. Addressing social determinants to improve patient care and promote health equity: an American College of Physicians Position Paper. *Ann Intern Med*. 2018;168:577-578.
3. Galea S, Tracy M, Hoggatt KJ, et al. Estimated deaths attributable to social factors in the United States. *Am J Public Health*. 2011;101:1456-1465.
4. CMS Framework for Health Equity. Accessed June 30, 2024. https://www.cms.gov/priorities/health-equity/minority-health/equity-programs/framework
5. FY 2024 Hospital Inpatient Prospective Payment System (IPPS) and Long-Term Care Hospital Prospective Payment System (LTCH PPS) Final Rule—CMS-1785-F and CMS-1788-F Fact Sheet. Accessed June 30, 2024. https://www.cms.gov/newsroom/fact-sheets/fy-2024-hospital-inpatient-prospective-payment-system-ipps-and-long-term-care-hospital-prospective-0
6. Social Determinants of Health. Accessed June 30, 2024. https://www.healthit.gov/health-equity/social-determinants-health
7. Yan AF, Chen Z, Wang Y, et al. Effectiveness of social needs screening and interventions in clinical settings on utilization, cost, and clinical outcomes: a systematic review. *Health Equity*. 2022;6:454-475.
8. Billioux A, Verlander K, Anthony S, et al.; Centers for Medicare and Medicaid Services. Standardized screening for health-related social needs in clinical settings: the accountable health communities screening tool. *NAM Perspect*. 2017;7. https://doi.org/10.31478/201705b
9. Committee on Integrating Social Needs Care into the Delivery of Health Care to Improve the Nation's Health, Board on Health Care Services, Health and Medicine Division, et al. *Integrating Social Care into the Delivery of Health Care: Moving Upstream to Improve the Nation's Health*. National Academies Press; 2019.
10. Drake C, Batchelder H, Lian T, et al. Implementation of social needs screening in primary care: a qualitative study using the

health equity implementation framework. *BMC Health Serv Res*. 2021;21:975.
11. Berg K, Doktorchik C, Quan H, et al. Automating data collection methods in electronic health record systems: a Social Determinant of Health (SDOH) viewpoint. *Health Syst (Basingstoke)*. 2023;12:472-480.
12. Tong ST, Liaw WR, Kashiri PL, et al. Clinician experiences with screening for social needs in primary care. *J Am Board Fam Med*. 2018;31:351-363.
13. Hu Y, Zuo X, Zhou Y, et al. Information extraction from clinical notes: are we ready to switch to large language models? arXiv [cs. CL]. 2024, preprint: not peer reviewed.
14. García-Barragán Á, Sakor A, Vidal ME, et al. NSSC: a neuro-symbolic AI system for enhancing accuracy of named entity recognition and linking from oncologic clinical notes. *Med Biol Eng Comput*. 2025;63:749-772.
15. Hu Y, Chen Q, Du J, et al. Improving large language models for clinical named entity recognition via prompt engineering. *J Am Med Inform Assoc*. 2024;31:1812-1820.
16. Sivarajkumar S, Tam TYC, Mohammad HA, et al. Extraction of sleep information from clinical notes of Alzheimer's disease patients using natural language processing. *J Am Med Inform Assoc*. 2024;31:2217-2227.
17. Lybarger K, Dobbins NJ, Long R, et al. Leveraging natural language processing to augment structured social determinants of health data in the electronic health record. *J Am Med Inform Assoc*. 2023;30:1389-1397.
18. Fu Y, Ramachandran GK, Dobbins NJ, et al. Extracting social determinants of health from pediatric patient notes using large language models: novel corpus and methods. In: Calzolari N, Kan M-Y, Hoste V, et al., eds. *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*. ELRA and ICCL; 2024:7045-56.
19. Keloth VK, Selek S, Chen Q, et al. Large language models for social determinants of health information extraction from clinical notes—A generalizable approach across institutions. medRxiv, preprint: not peer reviewed. 2024.
20. Yu Z, Peng C, Yang X, et al. Identifying social determinants of health from clinical narratives: a study of performance, documentation ratio, and potential bias. *J Biomed Inform*. 2024;153:104642.
21. Patra BG, Sharma MM, Vekaria V, et al. Extracting social determinants of health from electronic health records using natural language processing: a systematic review. *J Am Med Inform Assoc*. 2021;28:2716-2727.
22. Han S, Zhang RF, Shi L, et al. Classifying social determinants of health from unstructured electronic health records using deep learning-based natural language processing. *J Biomed Inform*. 2022;127:103984.
23. Guevara M, Chen S, Thomas S, et al. Large language models to identify social determinants of health in electronic health records. *NPJ Digit Med*. 2024;7:6.
24. Ong JCL, Seng BJJ, Law JZF, et al. Artificial intelligence, ChatGPT, and other large language models for social determinants of health: current state and future directions. *Cell Rep Med*. 2024;5:101356.
25. Gold R, Bunce A, Cowburn S, et al. Adoption of social determinants of health EHR tools by community health centers. *Ann Fam Med*. 2018;16:399-407.
26. Weiner S, Schwartz A, Altman L, et al. Evaluation of a patient-collected audio audit and feedback quality improvement program on clinician attention to patient life context and health care costs in the veterans affairs health care system. *JAMA Netw Open*. 2020;3:e209644.
27. Iott BE, Adler-Milstein J, Gottlieb LM, et al. Characterizing the relative frequency of clinician engagement with structured social determinants of health data. *J Am Med Inform Assoc*. 2023;30:503-510.
28. Weiner SJ. Contextualizing care: an essential and measurable clinical competency. *Patient Educ Couns*. 2022;105:594-598.
29. Hartzler AL, Xie SJ, Wedgeworth P, et al.; SDoH Community Champion Advisory Board. Integrating patient voices into the extraction of social determinants of health from clinical notes: ethical considerations and recommendations. *J Am Med Inform Assoc*. 2023;30:1456-1462. Published Online First: 21 March https://doi.org/10.1093/jamia/ocad043
30. Aldossari M. Participants' perceptions of privacy and data sharing regarding health-related data using artificial intelligence. *Asian J Sci Appl Technol*. 2023;12:6-12.
31. Khera R, Simon MA, Ross JS. Automation bias and assistive AI: risk of harm from AI-driven clinical decision support. *JAMA*. 2023;330:2255-2257.
32. Motulsky A, Denis J-L. *Investigating the Barriers to Physician Adoption of an Artificial Intelligence-Based Decision Support System in Emergency Care: An Interpretative Qualitative Study. Digital Personalized Health and Medicine*. IOS Press; 2020:1001-1005.
33. Mooghali M, Stroud AM, Yoo DW, et al. Trustworthy and ethical AI-enabled cardiovascular care: a rapid review. *BMC Med Inform Decis Mak*. 2024;24:247.
34. Richardson JP, Smith C, Curtis S, et al. Patient apprehensions about the use of artificial intelligence in healthcare. *NPJ Digit Med*. 2021;4:140.
35. Hovy D, Spruit SL. The social impact of natural language processing. In: *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*. Association for Computational Linguistics; 2016:591–8.
36. Park J, Saha S, Chee B, et al. Physician use of stigmatizing language in patient medical records. *JAMA Netw Open*. 2021;4:e2117052.
37. Liu Y, Wang W, Gao GG, et al. Echoes of biases: how stigmatizing language affects AI performance. arXiv [cs.AI]. 2023, preprint: not peer reviewed.
38. Oliver J, Reyes N, Harry L, et al. A scoping review of ethics considerations in clinical natural language processing. *JAMIA Open*. 2022;5:ooac039.
39. Butler ED, Morgan AU, Kangovi S. Screening for unmet social needs: patient engagement or alienation? *NEJM Catal Innov Care Deliv*. 2020;10.1. https://doi.org/10.1056/CAT.19.1037
40. Garg A, Boynton-Jarrett R, Dworkin PH. Avoiding the unintended consequences of screening for social determinants of health. *JAMA*. 2016;316:813-814.
41. Rogers AJ, Hamity C, Sharp AL, et al. Patients' attitudes and perceptions regarding social needs screening and navigation: multisite survey in a large integrated health system. *J Gen Intern Med*. 2020;35:1389-1395.
42. Takada S, Shen Z, Bourgois P, et al. A qualitative study of perceptions and preferences regarding social and behavioral risk screening among primary care patients. *J Gen Intern Med*. 2023;38:3171-3179.
43. De Marchis EH, Alderwick H, Gottlieb LM. Do patients want help addressing social risks? *J Am Board Fam Med*. 2020;33:170-175.
44. Rudisill AC, Eicken MGA, Gupta D, et al. Patient and care team perspectives on social determinants of health screening in primary care: a qualitative study. *JAMA Netw Open*. 2023;6:e2345444.
45. Hamity C, Jackson A, Peralta L, et al. Perceptions and experience of patients, staff, and clinicians with social needs assessment. *Perm J*. 2018;22:18-105.
46. Trochez RJ, Sharma S, Stolldorf DP, et al. Screening health-related social needs in hospitals: a systematic review of health care professional and patient perspectives. *Popul Health Manag*. 2023;26:157-167.
47. Herrera C-N, Brochier A, Pellicer M, et al. Implementing social determinants of health screening at community health centers: clinician and staff perspectives. *J Prim Care Community Health*. 2019;10:2150132719887260.

48. Arroyave Caicedo NM, Parry E, Arslan N, et al. Integration of social determinants of health information within the primary care electronic health record: a systematic review of patient perspectives and experiences. *BJGP Open*. 2024;8:BJGPO.2023.0155. https://doi.org/10.3399/BJGPO.2023.0155
49. Albert SM, McCracken P, Bui T, et al. Do patients want clinicians to ask about social needs and include this information in their medical record? *BMC Health Serv Res*. 2022;22:1275.
50. Nelson LA, Pennings JS, Sommer EC, et al. A 3-item measure of digital health care literacy: development and validation study. *JMIR Form Res*. 2022;6:e36043.
51. Truong KN, Hayes GR, Abowd GD. Storyboarding: an empirical determination of best practices and effective guidelines. In: *Proceedings of the 6th ACM Conference on Designing Interactive Systems—DIS '06*. ACM Press; 2006.
52. Earnshaw VA, Karpyn A. Understanding stigma and food inequity: a conceptual framework to inform research, intervention, and policy. *Transl Behav Med*. 2020;10:1350-1357.
53. Krug G, Drasch K, Jungbauer-Gans M. The social stigma of unemployment: consequences of stigma consciousness on job search attitudes, behaviour and success. *J Labour Market Res*. 2019;53:27.
54. Reilly J, Ho I, Williamson A. A systematic review of the effect of stigma on the health of people experiencing homelessness. *Health Soc Care Community*. 2022;30:2128-2141.
55. National Institute on Drug Abuse. Addressing the Stigma that Surrounds Addiction. National Institute on Drug Abuse. 2020. Accessed July 26, 2022. https://nida.nih.gov/about-nida/noras-blog/2020/04/addressing-stigma-surrounds-addiction
56. Kreuter MW, Thompson T, McQueen A, et al. Addressing social needs in health care settings: evidence, challenges, and opportunities for public health. *Annu Rev Public Health*. 2021;42:329-344.
57. Buitron de la Vega P, Losi S, Sprague Martinez L, et al. Implementing an EHR-based screening and referral system to address social determinants of health in primary care. *Med Care*. 2019;57:S133-S139.
58. Richie R, Ruiz VM, Han S, et al. Extracting social determinants of health events with transformer-based multitask, multilabel named entity recognition. *J Am Med Inform Assoc*. 2023;30:1379-1388.
59. Shah-Mohammadi F, Finkelstein J. Extraction of substance use information from clinical notes: generative pretrained transformer-based investigation. *JMIR Med Inform*. 2024;12:e56243.
60. Weiner BJ, Lewis CC, Stanick C, et al. Psychometric assessment of three newly developed implementation outcome measures. *Implement Sci*. 2017;12:108.
61. De Marchis EH, Hessler D, Fichtenberg C, et al. Part I: a quantitative study of social risk screening acceptability in patients and caregivers. *Am J Prev Med*. 2019;57:S25-S37.
62. CAHPS Clinician & Group Survey. Accessed June 30, 2024. https://www.ahrq.gov/cahps/surveys-guidance/cg/index.html
63. Hsieh H-F, Shannon SE. Three approaches to qualitative content analysis. *Qual Health Res*. 2005;15:1277-1288.
64. Berry C, Paul M, Massar R, et al. Social needs screening and referral program at a large US Public Hospital System, 2017. *Am J Public Health*. 2020;110:S211-S214.
65. Byhoff E, LeClair AM, Smith CN, et al. Designing an implementation strategy to increase health-related social needs screening: applying the PRISM framework in a resource-limited clinical setting. *Transl Behav Med*. 2024;14:197-205.
66. Adler-Milstein J, Redelmeier DA, Wachter RM. The limits of clinician vigilance as an AI safety bulwark. *JAMA*. 2024;331:1173-1174.
67. Wallace AS, Luther BL, Sisler SM, et al. Integrating social determinants of health screening and referral during routine emergency department care: evaluation of reach and implementation challenges. *Implement Sci Commun*. 2021;2:114.
68. Byhoff E, De Marchis EH, Hessler D, et al. Part II: a qualitative study of social risk screening acceptability in patients and caregivers. *Am J Prev Med*. 2019;57:S38-S46.
69. Osheroff JA, Teich JM, Middleton B, et al. A roadmap for national action on clinical decision support. *J Am Med Inform Assoc*. 2007;14:141-145.
70. Care Everywhere, Epic. Accessed June 30, 2024. https://www.epic.com/careeverywhere/
71. He Z, Pfaff E, Guo SJ, et al. Enriching real-world data with social determinants of health for health outcomes and health equity: successes, challenges, and opportunities. *Yearb Med Inform*. 2023;32:253-263.
72. Taksler GB, Dalton JE, Perzynski AT, et al. Opportunities, pitfalls, and alternatives in adapting electronic health records for health services research. *Med Decis Making*. 2021;41:133-142.
73. Kim MK, Rouphael C, McMichael J, et al. Challenges in and opportunities for electronic health record-based data analysis and interpretation. *Gut Liver*. 2024;18:201-208.
74. Jamieson MK, Govaart GH, Pownall M. Reflexivity in quantitative research: a rationale and beginner's guide. *Soc Personal Psychol Compass*. 2023;17:e12735.
75. Nazer LH, Zatarah R, Waldrip S, et al. Bias in artificial intelligence algorithms and recommendations for mitigation. *PLOS Digit Health*. 2023;2:e0000278.
76. Ratwani RM, Sutton K, Galarraga JE. Addressing AI algorithmic bias in health care. *JAMA*. 2024;332:1051-1052.
77. Dankwa-Mullan I. Health equity and ethical considerations in using artificial intelligence in public health and medicine. *Prev Chronic Dis*. 2024;21:E64.
78. Healy M, Richard A, Kidia K. How to reduce stigma and bias in clinical communication: a narrative review. *J Gen Intern Med*. 2022;37:2533-2540.
79. Triplett C, Fletcher BJ, Taitingfong RI, et al. Codesigning a community-based participatory research project to assess tribal perspectives on privacy and health data sharing: a report from the Strong Heart Study. *J Am Med Inform Assoc*. 2022;29:1120-1127.
80. Portnoy GA, Colon R, Gross GM, et al. Patient and provider barriers, facilitators, and implementation preferences of intimate partner violence perpetration screening. *BMC Health Serv Res*. 2020;20:746.
81. Theis RP, Blackburn K, Lipori G, et al. Implementation context for addressing social needs in a learning health system: a qualitative study. *J Clin Transl Sci*. 2021;5:e201.
82. Zhang Z, Kmoth L, Luo X, et al. User-centered system design for communicating clinical laboratory test results: design and evaluation study. *JMIR Hum Factors*. 2021;8:e26017.
83. Wong JIS, Steitz BD, Rosenbloom ST. Characterizing the impact of health literacy, computer ability, patient demographics, and portal usage on patient satisfaction with a patient portal. *JAMIA Open*. 2019;2:456-464.
84. Dykstra S, MacDonald M, Beaudry R, et al. An institutional framework to support ethical fair and equitable artificial intelligence augmented care. *NPJ Digit Med*. 2025;8:84.
85. Langevin R, Berry ABL, Zhang J, et al. Implementation fidelity of chatbot screening for social needs: acceptability, feasibility, appropriateness. *Appl Clin Inform*. 2023;14:374-391.
86. Pandey M, Maina RG, Amoyaw J, et al. Impacts of English language proficiency on healthcare access, use, and outcomes among immigrants: a qualitative study. *BMC Health Serv Res*. 2021;21:741.
87. Al Shamsi H, Almutairi AG, Al Mashrafi S, et al. Implications of language barriers for healthcare: a systematic review. *Oman Med J*. 22020;35:e122.
88. Rogers CK, Parulekar M, Malik F, et al. A local perspective into electronic health record design, integration, and implementation of screening and referral for social determinants of health. *Perspect Health Inf Manag*. 2022;19:1g.

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