Developing an AI Tool to Derive Social Determinants of Health for Primary Care Patients: Qualitative Findings From a Codesign Workshop

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VISUAL ABSTRACT

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PURPOSE Information about social determinants of health (SDOH) is essential for primary care clinicians in the delivery of equitable, comprehensive care, as well as for program planning and resource allocation. SDOH are rarely captured consistently in clinical settings, however. Artificial intelligence (AI) could potentially fill these data gaps, but it needs to be designed collaboratively and thoughtfully. We report on a codesign process with primary care clinicians to understand how an AI tool could be developed, implemented, and used in practice.

METHODS We conducted semistructured, 50-minute workshops with a large urban family health team in Toronto, Ontario, Canada asking their feedback on a proposed AI-based tool used to derive patient SDOH from electronic health record data. An inductive thematic analysis was used to describe participants' perspectives regarding the implementation and use of the proposed tool.

RESULTS Fifteen participants contributed across 4 workshops. Most patient SDOH information was not available or was difficult to find in their electronic health record. Discussions focused on 3 areas related to the implementation and use of an AI tool to derive social data: people, process, and technology. Participants recommended starting with 1 or 2 social determinants (income and housing were suggested as priorities) and emphasized the need for adequate resources, staff, and training materials. They noted many challenges, including how to discuss the use of AI with patients and how to confirm their social needs identified by the AI tool.

CONCLUSIONS Our codesign experience provides guidance from end users on the appropriate and meaningful design and implementation of an AI-based tool for social data in primary care.

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INTRODUCTION

Artificial intelligence (AI) has increasingly become part of our society, including in health care. The use of AI in primary care, in particular, has the potential for widespread impact on patient care and clinician workload, as primary care is where the majority of patient visits occur within the Canadian health care system.[1,2] A high-priority task for AI identified by primary care clinicians and patients during recent pan-Canadian consultations was to support automated charting, including the collection and verification of patient information in their electronic health record (EHR).[3] This practice would help alleviate clinician burnout and liberate both time and cognitive freedom for direct patient care.[3] Despite technologic advances, however, successful implementation of AI-based tools into primary care practice remains challenging because of a variety of factors such as lack of system readiness, bias in data and AI algorithms, and the need for a better understanding of people as "technology enablers."[4] Codesigning AI tools with end users is an important strategy that leads to better acceptability and adoption of the tools in clinical settings.[5] This process also ensures that AI is addressing an important and timely problem identified by primary care teams, while building trust and ensuring effective integration into clinical workflow.

This article describes a real-world example from the St Michael's Hospital Academic Family Health Team (FHT), an urban interprofessional primary health

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care team who recently initiated a project to explore the development of an AI-based tool to derive information about their patients' social determinants of health (SDOH). Patient SDOH data are necessary for the provision of comprehensive, personalized medicine, yet this information is often not available to health care teams.[6] As part of a codesign process, the objective of this study was to understand the FHT's preferences on the integration and presentation of a machine learning–based tool that could generate SDOH information about their patients from existing EHR data. This work is novel in Canada, as very few primary care practices have access to a reference set of SDOH data for their patients, as well as the technical infrastructure and expertise to conduct AI research.

METHODS

The FHT has distributed an SDOH questionnaire to their patients since 2013; however, information is still missing for nearly two-thirds. The FHT wanted to explore whether AI could fill information gaps by deriving SDOH data from its EHR data. The Design Council's Framework for Innovation[7] guided this process to ensure the AI tool was relevant and useful for their needs. The first phase (discovery) included interviews with primary care clinicians and health system leaders in Ontario, Canada.[8] Those findings informed the second phase (define) to develop a strategy for using machine learning to derive SDOH data from EHR data (work in progress). The third phase (develop), described in this article, consisted of codesign workshops with the FHT to gain a better understanding of their preferences for the AI tool and how it might work best in practice.

Study Sample

Participants were recruited through e-mail invitations circulated to all FHT clinicians, allied health care professionals, clinic staff, and medical residents. The FHT provides care across 5 practice sites in the downtown core of Toronto, Ontario, Canada's largest city with an estimated population of more than 3 million people.[9] It is part of a teaching network within the University of Toronto and serves approximately 50,000 patients, many of whom experience social and economic challenges.

Data Collection

We offered 4 workshops, each lasting 50 minutes, at the convenience of participants from May to June 2023; we held 3 in person at practice sites and conducted 1 virtually (Supplemental Appendix). The workshops were facilitated by a postdoctoral fellow embedded in the FHT with experience in primary care EHR data research (S.G.) and an FHT family medicine resident (S.L.).

The workshops began with an overview of the project, including a short tutorial on machine learning and details about ongoing work to test the use of AI to derive SDOH from EHR data. Participants briefly discussed what SDOH data were available and used for patient care. Next, a short, animated example was shown, demonstrating how the AI tool might function in a mock patient visit. This led into a brainstorming exercise that was guided by a sociotechnical systems framework for the application of AI in health care delivery[10] and centered on 3 areas: (1) who are the people who should access and/or act on AI-derived social data, (2) what is the optimal process for integrating the tool into clinical workflow, and (3) what should the technology look like or achieve. Lastly, participants were asked about perceived barriers and facilitators when implementing this AI tool. We used a deliberative dialog technique to facilitate meaningful feedback that could be incorporated into the development of the AI tool.[11,12] A demographic survey captured participants' personal and practice characteristics (gender, age, language, role, years in practice). Written consent was obtained from each participant before the workshop and a $25 gift card was provided as appreciation for participants' time.

Data Analysis

A voice-recording device was used to capture audio from in-person workshops and Zoom (Zoom Video Communications, Inc) was used to record the online workshop. The audio data were transcribed using Otter.ai software (Otter.ai Inc), and the transcript was reviewed alongside the audio by one of the workshop facilitators (S.G.) to verify the accuracy and edit as needed. An inductive thematic analysis[13] was conducted to classify the discussions and ideas generated from the workshops. The data were categorized independently by 2 study team members (S.G., S.L.), then an iterative process was used to ensure alignment, where the analysts would meet to discuss, compare, and reach consensus on codes and themes.

Coding and analysis of the transcribed text was conducted using NVivo 12 version 12.6.0.959 (QSR International). Qualtrics (Silver Lake Technology Management, LLC) was used for the electronic demographic survey.

This study was reviewed and approved by the Unity Health Toronto Research Ethics Board (REB No. 22-036).

RESULTS

In total, 15 members of the St Michael's Hospital Academic FHT participated across the 4 workshops. Of the 12 FHT members who completed the demographic survey, the large majority were female (75%) and aged from 30 to 44 years (67%) (Table 1).

How Do Participants Currently Access and Use SDOH Information?

Participants reported having access to some SDOH information in the personal history and/or Cumulative Patient Profile sections of the EHR, which is obtained by asking patients directly. SDOH data are also captured through the Health Equity Questionnaire[6] and becomes part of the

Table 1. Participant Characteristics (N = 12)

Characteristic	Value
Gender, No. (%)	
Women	9 (75.0)
Men	3 (25.0)
Age group, No. (%)	
≤29 years	3 (25.0)
30-44 years	8 (66.7)
45-59 years	1 (8.3)
Main role, No. (%)	
Family physician	4 (33.3)
Practice nurse (eg, RN, LPN)	3 (25.0)
Nurse practitioner	2 (16.7)
Clinic lead or manager	1 (8.3)
Social worker	1 (8.3)
Income security health promoter	1 (8.3)
Time in clinical practice, mean (SD), y	6.9 (9.2)
Time in nonclinical role, mean (SD), y	3.3 (3.8)
General knowledge of AI, No. (%)	
Minimally knowledgeable	7 (58.3)
Moderately knowledgeable	4 (33.3)
Very knowledgeable	1 (8.3)

AI = artificial intelligence; LPN = licensed practical nurse; RN = registered nurse.

patient record. Participants reported, however, that patient social data were often inconsistent, difficult to search for, and incomplete for most. During patient intake interviews, clinicians generally asked about employment, education, social supports, immigration, and other determinants as appropriate. Most participants felt confident that gender identity and sexual orientation were kept up to date, but there was uncertainty about how frequently other SDOH were updated.

Participants spoke of the importance of having access to SDOH information for providing tailored and respectful patient care. As one clinician articulated, "You might not assume that they have a lot of, maybe, resourcefulness in terms of like ... what kind of instructions you give them, how to proceed with the treatment or how to access other resources."

There was a clear desire to have information about patients' income, employment, and health insurance to inform prescribing decisions for those who may not have medication benefits (eg, choosing a lower-cost drug) or to provide free supplies, such as dressing changes for wound care. Knowledge of sexual orientation helped provide appropriate education, screening, and resources for sexually transmitted infections to their patients. Information on preferred spoken language was also seen as valuable to determine if interpreter services were required during visits, to prompt clinicians into giving shorter, simpler instructions to patients, or to allocate extra appointment time.

Implementation and Use of AI-Derived SDOH

As previously noted, our brainstorming exercise elicited participants' preferences in 3 areas related to the implementation and use of an AI tool to derive social data: people, process, and technology. Preferences in these domains, which are based on a sociotechnical systems framework for the application of AI in health care delivery,[10] are detailed below and summarized in Table 2.

People

Participants expressed various preferences on who should have access to AI-derived social data and who is responsible for acting on these data (Table 2). There was consensus that anyone in the patient's direct "circle of care" or who already had access to the patient record should be able to view the AI-derived social data, including physicians, nurse practitioners, nurses, and social workers. There was uncertainty whether patients and/or clerical staff should have access; some participants worried the information could bias staff when communicating with patients, although others noted these data are necessary to address people by preferred pronouns and support them with transportation needs or logistics.

The most responsible provider (usually the family physician) was identified as the person to lead any action required if a major social need was flagged. Several participants argued that anyone involved with patient care should be responsible for acting but in varying capacities according to different clinical roles (eg, physician, nurse, social worker). The difficulties of deciding when and how to act on identified social needs were expressed by many participants. Further, participants were unclear if they had a legal obligation to act on a social need flagged by the tool, as this was viewed as "extra information." Participants were open to providing access to AI-derived social data to personnel outside the care team for specific uses that would benefit patients (eg, quality improvement, research), but strongly opposed other private/third-party entities such as insurance companies, housing agencies, or other commercial organizations having access of any kind.

Process

Participants recommended a pilot implementation of the AI tool using a slow, scaled-back approach focused on 1 or 2 social determinants initially, accuracy testing by confirming the AI output with patients, anticipating and preparing guidance according to the AI output, and gathering feedback from clinicians (Table 2). All participating sites suggested starting with income and housing as 2 important and actionable determinants.

Several participants questioned why AI would be used rather than relying on self-report surveys, which would be easier to discuss with patients. It was agreed, however, that it was not feasible to collect SDOH information from all patients in the practice and a balance was needed between using AI and relying on patient self-report. There was recognition that because the AI output was unlikely to be 100%

Table 2. Using a Sociotechnical Systems Framework for the Application of AI in Health Care Delivery to Describe Participant Preferences on People, Process, and Technology

Domain	Themes and Subthemes	Salient Quotes
People	Who should have access to AI-derived social data? • "Circle of care" team or anyone already having access to patient record • Uncertainty whether clerical staff and/or patients should have access • Appropriate to be accessed for quality improvement, practice-related purposes (eg, program planning/development, practice management, resource allocation) and research • No access for private/third-party entities outside of circle of care (eg, insurance companies, housing agencies, any commercial organization)	"I think it's very important to really understand those vulnerabilities linked to the social determinants to, kind of, allocate your resources as a provider, how much time investment is required to cater to the specific needs. So yeah, definitely, that information should be available to all the providers in the family health team, so they can provide that targeted, tailored care."
	Who should take action if a social need is identified through the AI tool? • Should be led by most responsible provider (usually the family physician) • Varying levels of action for different team members involved with patient care (eg, social workers, nurses) • Many expressed the challenge of deciding when and how to act on an identified social need	"I think MRP is the most responsible. But I think anybody that sees that information could take a step to act on it. So you know, if they they're meeting with nursing that day, and they notice something, and it's something that might be appropriate for a referral to a social worker, the income program, you know, we get referrals from doc, from nurses, everybody does."
Process	Start with pilot implementation • Focus on 1 or 2 social determinants initially • Verify AI response with patients to establish accuracy of the tool • Anticipate guidance or management required according to AI output • Obtain feedback from clinicians at end of pilot phase to measure satisfaction and usefulness	"How would I go about contacting the patient and saying, 'Hey, the computer thinks you might have low income? What's your income?' How would that communication piece go?"
	Workflow considerations • Patients were to verify/confirm social need once identified, but participants were uncertain how to do this without concerning their patients • Additional staff time and resources needed • Participants desired a balance between asking for SDOH information directly from patients (eg, surveys) and using AI to derive it where missing • Participants indicated that consent should be sought from patients to use AI to derive social information (either direct or implied)	"I can't imagine telling all my patients that AI is going to be reviewing their charts. They would absolutely never see me again." "... for an individual social worker or physician, I think this would add work to our day. But probably provide better care. There's a chance that we'd maybe solve their homelessness earlier and then later not have to deal with terrible mental health issues. So I guess that could be time gained. But overall, I suspect it would cause more work, which isn't bad, because it's probably for the best of the patient."
	Activities or initiatives to support the adoption and integration of the AI tool • Regularly scheduled meetings to discuss AI tool, implementation, and evaluation • Use team to develop the algorithms alongside FHT staff who are ideally knowledgeable about the clinical environment • Additional hours/staffing for nursing, physician assistant, and/or social work • More staff for income and housing supports • Ensure free tax clinics for patients are available • Hire additional community health workers to conduct telephone check-ins with vulnerable patients • Ensure good connections and referral pathways to community agencies (ie, housing, income, gender transitioning) • Plans or recommendations for physicians managing a large volume of messages flagging social needs or concerns identified by the AI tool, which would then need to be sorted and verified; this is especially pertinent for the FHT, as they provide care for a large proportion of patients who would potentially be flagged with social needs or concerns • Meaningful and long-term engagement with patients and communities • Support from leadership and clinic management	"But if you want it to be more actionable, then you'd have to have scheduled meetings and have people suited to the clinical environment to help develop algorithms with the staff. So [you'd need] personnel to help do that. And ideally, like nursing and social work hours or physician assistant hours, but that's like in a dream world, because that's a huge cost." "It would be something I feel like management could be involved in supporting, whether it's programs run by the nurses or something, but like we would need support from management and leadership."

continues

AI = artificial intelligence; EHR = electronic health record; FHT = family health team; MRP = most responsible provider; SDOH = social determinants of health.

Note: Framework was developed by Salwei and Carayon.[9]

Table 2. Using a Sociotechnical Systems Framework for the Application of AI in Health Care Delivery to Describe Participant Preferences on People, Process, and Technology *(continued)*

Domain	Themes and Subthemes	Salient Quotes
Technology	What SDOH data should be included in the AI tool? • All participants agreed on housing and income insecurity as priorities • Other SDOH suggested by participants: drug benefits/coverage and other medical coverage (eg, relevant to which medications are prescribed and allied health referrals, such as physiotherapy and massage therapy), sexual orientation, gender, country of origin, education, food insecurity, social isolation (particularly for elderly patients or immigrants), ability to navigate the health care system, health care access • Date associated with each determinant	"Income is such a broad category, that kind of ties to so many different aspects like food security, housing, job security. And usually, it's almost like, it's so interchangeable, like, because of the health, you know, all these things are affected, or because of the income, the health is affected. So it just relates so well. So that [income] will be a very broad theme that should be given good focus." "... Sure, it takes a lot of work and resources to get something like this going. So if we know that it's this ... and then maybe we move on to another one. We'd say like, 'Oh, I really like housing and income, it's really important. It's helpful.' And maybe the rest of it is like, we're okay to do without or something, we can just figure that out. And it's less critical or maybe down the road." "Like the prescribing, you briefly glance at the side to see 'Do they have insurance coverage?', like 'What did they do for work?' all of like micro pieces of information that guide your decision with income and employment."
	How could this AI tool be most useful? • Embedded in patient record/EHR • AI tool to gather and summarize important information from patient record • Ensure tool provides actionable output • Monitor changes in patient status (eg, housing, income) and alert if potential challenge arises • Automatic prompts for specific appointment or referral related to social work, income support, telephone support, or other resources • AI tool output connected to local, evidence-based solutions	"I think kind of a change in status could also be interesting, you know, someone who's kind of been as, let's say, middle of the road, and then all of a sudden, the algorithm predicts that there's been a significant drop in their income security, housing security, etcetera. And flagging that to the provider, kind of using that as a prompt to have a discussion around that. I think that could also be a pretty useful tool." "But if we could use it for programming, like, if we find that like, a lot of our patients are low income and not filing their taxes, then we could send them directly to like tax clinics and make sure that those get done."

AI = artificial intelligence; EHR = electronic health record; FHT = family health team; MRP = most responsible provider; SDOH = social determinants of health.

Note: Framework was developed by Salwei and Carayon.[9]

accurate, a validation process with patients was required. It was left undecided who would be responsible for this; one suggestion was to use the AI output as a "check-in" prompt, which could initiate a telephone call or follow-up with patients to ask about their current situation. Participants also felt that they would need to explain to patients why they were asking and what information in the record led them to this determination, although some participants were uneasy about how their patients would respond.

There was universal concern about the additional staff time and resources that this tool could impose, especially to confirm accuracy with patients and with respect to the new workflow created by the tool (eg, extra appointment time, additional visits). A tension existed between implementing a tool that would place a larger burden on busy clinicians and staff, and recognizing that this tool would likely improve patient care. Nevertheless, participants expressed an interest in trialing the tool and offered a variety of suggestions that would support its integration (Table 2).

Technology

As the workshop discussion turned to the technology itself (Table 2), participants agreed it was important to have the AI-derived social data presented simply and made available in the patient record to view and use as needed, either in the Cumulative Patient Profile (main summary of conditions)

Table 3. Barriers and Facilitators for the Use of AI-Derived Social Data as Reported by Participants

Domain	Barriers	Facilitators
People	• Ensuring patient privacy, especially for patients who have expressed they do not want their health information shared outside the circle of care • Use of AI might lead to patient mistrust • Some clinicians expressed distrust in AI, especially the ability for it to be accurate • Clinic staff who do not like technology or are unfamiliar with technology are less likely to adopt • Use of AI might lead to patient mistrust in their clinicians • Possible public perception of AI as going through their sensitive medical information or disclosing this information outside of the clinical care circle	• Provide 1-page summary for staff about AI tool • Make available 1-page lay summary for patients about AI tool • Don't call it AI • Demonstrate the benefit to patients of allowing their clinicians access to AI-derived social data • Have an AI champion at each FHT site to advocate for its use and to problem solve, and ensure champion is well supported • Ensure FHT leadership and clinic management support tool and integration into clinical processes • Have a trustworthy team managing the AI tool who are familiar to the FHT
Process	• Lack of knowledge among participants about how the AI tool works or what data are being used • Differing opinions about the AI tool and how it should be used • Too much additional staff time and resources required • Overreliance on AI may erode clinical skills and decision making over time	• AI-derived data presented consistently and as a simple summary • AI-derived data easy to find and access (eg, in CPP; not a lot of clicks to get to it) • AI should not slow down the EHR • AI tool should require little to no learning curve • Ensuring adequate practice staffing to manage increase in workload • Regular engagement needed with FHT to explain how the AI tool works (eg, site visits, communication, embedding of presentations into regular clinic meetings) • Circulate background information about AI tool (eg, its performance, validity) for reference
Technology	• AI tool requiring extra technology or hardware • EHR data used for the AI seen as not reliable or timely • Variation in the data (eg, type and amount of information entered) could cause bias • Accuracy of AI tool in correctly classifying patients • Accurate representation of the data in the AI tool	• Display accuracy metrics (eg, percentages) • More/better data collection within the patient record (to help improve accuracy, trust) • Automatically updating AI output or EHR if circumstances change (eg, date-stamped)

AI = artificial intelligence; CPP = Cumulative Patient Profile; EHR = electronic health record; FHT = family health team.

or with a custom SDOH button to display a summary of the AI output.

There were many examples provided of how the AI tool could be used in practice, such producing simple summaries of pertinent patient information so that clinicians could act quickly instead of spending time scrolling through notes or potentially overlooking important information. Another suggestion was to have the tool monitor social circumstances over time to make note of improvements or declines. Participants also requested the ability to manually correct the AI output if it was found to be inaccurate after confirming with patients. All participants desired that the AI tool assist with actionable tasks, ideally matched with evidence-based, local solutions; however, this aim was acknowledged as being challenging and time consuming. For instance, participants described an ideal use case where the tool could automatically prompt a referral to or follow-up appointment with social work or income support, especially if this could free up time to manage other pressing medical concerns during the visit.

Participants also described several relevant non–patient-facing uses of the AI tool that would be desirable, as long as it would benefit patients; these uses included quality improvement, program planning, resource allocation, designing patient education sessions, streamlining workflow, prioritizing patients for initiatives such as wellness telephone calls, providing tailored information on how to access social supports (eg, tax assistance clinics), performing research, and conducting advocacy.

Barriers and Facilitators

The barriers and facilitators for implementing and using the AI tool reported by participants are summarized in Table 3. Many concerns centered around biases in the data and AI, as well as maintaining patient confidentiality and trust. There was considerable worry that the AI tool could perpetuate discrimination or create racial biases, which might affect clinical decisions or communication with patients. Participants also mentioned the selection bias that could occur if patients were required to provide explicit consent for use of the AI tool—for instance, patients who might benefit from additional social resources may be less willing to permit the use of AI on their data.

DISCUSSION

Findings in Context

The codesign workshops described here provided a guiding path for our continued development of an AI tool for social data and eventual integration into the FHT's practice. This "last mile of implementation" into real-world clinical settings is arguably the most difficult and remains largely unsolved, even with AI systems that are highly accurate.[14,15] Hesitation for implementing AI tools may stem from one of the predominant tensions that emerged from the workshop discussions, where AI was perceived as a time-saving tool that could alleviate clinician workload, but it was also anticipated to create additional burden on the practice. A number of questions still remain and will require further investigation, including workflow specifics, staffing considerations, and the patient verification process.

Participants in this study all mentioned concerns with data quality and the potential for bias; clinicians, as both data creators and users, are acutely aware of the possibilities and limitations of EHR data when used for secondary purposes. Given the current challenges with data quality and algorithms that are unlikely to perform perfectly, the ideal balance may require limiting the AI-derived SDOH data for aggregate, clinic-level purposes (eg, planning, resourcing) rather than using it for direct patient care. Patient self-report of SDOH should ideally continue, not only to support personalized care with individual-based solutions to social needs but also as a true reference standard for any secondary analyses in the future.

The challenges reported by participants are consistent with those in other studies on AI use in primary care, such as system readiness; ethical, legal, and social implications; and balancing the value of adopting AI against the large time and staff commitment.[4,5] Broad strategies to ameliorate these concerns include codesign/cocreation, iterative implementation, and continual evaluation.[4,5] More specifically, participants indicated their preference to start slowly with a small pilot project; to ensure regular communication between staff and researchers; to better define the workflow once a social need was identified; and to understand and address all resourcing implications.

Finally, participants expressed uncertainty about how to talk to patients about the use and outcomes of AI applied to their data and what a feasible consent model might look like. A recent review emphasized the necessity of moving machine learning models from ones merely being interpretable to ones that provide justifiability,[16] for instance, rather than using AI to indicate whether a patient is experiencing a particular issue (eg, poverty), the tool should also provide the reasoning (eg, unemployment record found, key words identified in progress notes). This also highlights the importance of patient and clinician educational resources for AI and digital health, which could facilitate more informed conversations around the use of AI in clinical settings and possibly allay concerns about the technology itself.

Limitations

This study reflects the perspectives of one primary care group in Toronto, Ontario and may not be applicable to all primary care teams, health care settings, or regions. The patient-related barriers and facilitators were reported by participants based on their experiences and conversations with patients, and may not reflect concerns from patients themselves. Lastly, we likely had underrepresentation of social workers and other staff/allied health care professionals who are primarily responsible for addressing aspects of SDOH (eg, housing, food insecurity, transportation), which could affect the design of workflow processes.

Conclusions

The use of AI in health care settings is growing, with many possible applications and purposes. It is critical to engage and codesign with end users throughout the entire process of AI ideation and development. Our study highlights the preferences of one large urban academic family health team on an AI tool to derive social data for their patients. A future study is needed to formally evaluate the implementation of the AI tool once it is ready for deployment.

Read or post commentaries in response to this article.

Key words: primary care; artificial intelligence; codesign; qualitative methods; social factors in health and health care; practice-based research; vulnerable populations

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Supplemental materials

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