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Research and Applications

Characterizing the relative frequency of clinician engagement with structured social determinants of health data

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ABSTRACT

Objective: Electronic health records (EHRs) are increasingly used to capture social determinants of health (SDH) data, though there are few published studies of clinicians' engagement with captured data and whether engagement influences health and healthcare utilization. We compared the relative frequency of clinician engagement with discrete SDH data to the frequency of engagement with other common types of medical history information using data from inpatient hospitalizations.

Materials and Methods: We created measures of data engagement capturing instances of data documentation (data added/updated) or review (review of data that were previously documented) during a hospitalization. We applied these measures to four domains of EHR data, (medical, family, behavioral, and SDH) and explored associations between data engagement and hospital readmission risk.

Results: SDH data engagement was associated with lower readmission risk. Yet, there were lower levels of SDH data engagement (8.37% of hospitalizations) than medical (12.48%), behavioral (17.77%), and family (14.42%) history data engagement. In hospitalizations where data were available from prior hospitalizations/outpatient encounters, a larger proportion of hospitalizations had SDH data engagement than other domains (72.60%).

Discussion: The goal of SDH data collection is to drive interventions to reduce social risk. Data on when and how clinical teams engage with SDH data should be used to inform informatics initiatives to address health and healthcare disparities.

Conclusion: Overall levels of SDH data engagement were lower than those of common medical, behavioral, and family history data, suggesting opportunities to enhance clinician SDH data engagement to support social services referrals and quality measurement efforts.

Key words: social determinants of health, electronic health records, engagement, documentation, review, readmissions

BACKGROUND AND SIGNIFICANCE

Motivated by shifts towards value-based payment and efforts to improve health outcomes, US healthcare organizations are increasingly screening patients for unmet health-related social risks such as food, housing, and transportation insecurity, which are downstream manifestations of broader social (SDH), economic, and political determinants of health.[1–7] While SDH data in the electronic health record (EHR) have traditionally been captured in free-text clinical notes, there is a push to include them in discrete structured data fields.[8] The standardization and accessibility of discrete documentation make these data more accessible to clinicians, enabling them to engage with SDH data by documenting and/or reviewing. Structured SDH data capture can also support population health management efforts to understand the prevalence of social risk factors in patient populations. Additionally, discrete documentation of data stored in computable formats can be used to trigger clinical decision support (CDS) tools that suggest adjustments to medical care decisions based on patients' social circumstances[9,10] or used with community resource referral platforms (CRRPs)[11] to address needs by providing referrals to community-based organizations (CBOs).[12–16]

Social needs adversely impact health outcomes,[17–19] including hospital readmission risk.[20–23] Screening and subsequent programs to address social needs in healthcare settings may create additional opportunities for social needs to be identified and addressed, and to tailor care plans to circumvent social barriers that contribute to worse health outcomes. For example, knowledge that a patient has transportation needs can help a care team to either provide that patient with transportation vouchers in order to travel to a follow-up appointment, or to arrange telehealth follow-up so that the patient does not have to navigate coming to an in-person appointment. Engaging with SDH information in EHRs should ideally help clinicians adapt their discharge planning to take into account patient social barriers. However, the association between SDH data engagement and readmission risk, a particularly salient clinical outcome given the high cost of hospital readmissions,[24,25] is currently unknown. Engagement represents a different concept than the mere presence or absence of medical and social risk factors, as it signifies a clinician interacting with the data in a measurable way. Given established associations between SDH and readmission,[20–23] SDH data engagement, and subsequent social care to address patients' needs, may decrease the likelihood of preventable readmissions.

Additionally, it is unclear how much clinicians engage with SDH data relative to other EHR data. Using data from the EHR audit log, clinician engagement with SDH data and other forms of common clinical data, including medical, family, and behavioral history, can be quantitatively measured. Measures of engagement with each of these types of data may be useful in predicting readmissions, especially if engagement is a proxy for clinicians' knowledge of patient social circumstances and subsequent efforts to tailor medical decision making to overcome social barriers to care or target interventions to prevent avoidable readmissions. Prior work has shown that while discrete social data fields are now widely available in EHRs, levels of SDH data engagement are low.[26] Indeed, prior work found that discrete patient social history question fields were used during only 0.03% of hospitalizations and discrete social documentation in the problem list occurred during 0.09% of hospitalizations, though other types of free-text social history documentation fields were more frequently used (patient social history text used during 12.1% of hospitalization and social work notes written during 27.5% of hospitalizations).[26] However, previous work only examines absolute

levels of engagement; no study directly compares the frequency of documentation and review of discrete SDH data relative to other common types of discrete clinical information, such as medical, family, and behavioral history. Understanding the differences in clinician engagement with different types of data can help determine whether discrete SDH fields are underutilized relative to other data fields. Substantially lower frequency of SDH data engagement relative to common medical history data may indicate missed opportunities to address patients' social needs and to tailor medical care accordingly.

To the extent that we observe lower levels of SDH data engagement relative to common medical history data, we can inform efforts to increase engagement by identifying characteristics associated with lower and higher levels of use. Insights from *patient characteristics* can shed light on whether SDH data engagement is occurring equitably across patient populations to avoid creating or perpetuating health inequities.[27] For example, demographic groups with lower relative rates of SDH data engagement may be subject to inequities because they would not benefit from referrals to CBOs and/or from medical care adjusted to account for social circumstances. Insights from *encounter characteristics* can shed light on whether specialty or practice-based workflows contribute to any observed differences.[28] Ultimately, understanding SDH data engagement is valuable because it should facilitate better patient management and improved health outcomes by informing clinicians about social circumstances relevant to providing care.

OBJECTIVE

We explored associations between clinician engagement with SDH and hospital readmissions. We also sought to compare the frequency of clinician engagement with discrete SDH data (via documentation and/or review of these data) to the frequency of other common types of discrete medical history information (medical, family, and behavioral history fields). Finally, we sought to identify patient and encounter characteristics associated with higher levels of SDH data engagement. We focused on an inpatient population and activities during hospitalizations because it afforded discrete time-bounded windows in which to observe data engagement and during which, ideally, patient medical, family, behavior, and social histories are reviewed. We conducted this study at UCSF Health, a large academic medical center using an Epic EHR, and created measures of clinician data engagement behaviors that may be generalized to a wide variety of clinical settings. Taken together, our results offer new insights into the implementation and value of discrete capture of SDH information in EHRs.

METHODS

Setting and study sample

The study sample included all inpatient encounters at the four UCSF Health hospitals between February 1, 2018 and April 30, 2021. For each hospitalization, we extracted metadata capturing whether discrete SDH, medical history, family history, and behavioral history documentation occurred (from data element-specific tables) and metadata capturing whether discrete SDH/medical/family/behavioral history documentation was reviewed (from audit log tables) from Epic's reporting database (Clarity). We also extracted patient demographics (age, gender, race, ethnicity, insurance class, whether the patient had a UCSF primary care physician [PCP]) and hospitalization characteristics

(admission and discharge time, admission source, and discharge location). For our readmission analysis, we focused specifically on patients' first hospitalization and subsequent readmission, if present, at UCSF Health.

History activity domains

Our analysis focused on user behavior within the History Activity,[29] the Epic tool designed for discrete data documentation and review of medical, family, behavioral, and SDH history. In our institution's EHR instance of the History Activity, users document relevant medical and family history discrete items using the types of fields listed in Table 1. Some of the behavioral and SDH fields are presented as radial buttons and text fields mapped to specific history items and screening questions, whereas others are available as pages within the patient's "History" tab. The range of fields available in each history domain is shown in Table 1. Screen captures of the History Activity user interface are shown in Supplementary Appendices SA–SD.

History activity discrete data engagement measures

We created measures of clinician engagement with History Activity data, separately for each history domain (SDH, medical, family, and behavioral). These measures capture whether there was one or more instances in which a clinician documented (either via adding or editing at least one history field such as those in Table 1) or reviewed (as indicated by the user clicking the "Mark as Reviewed" button associated with the landing page on which the field exists) data between the time of admission and the time of discharge.

Because History Activity data could have been documented during an inpatient or ambulatory encounter prior to the index hospitalization, we created another set of clinician engagement measures limited to hospitalizations of patients that had prehospitalization documentation. For example, if a given patient had a medical history field and an SDH field documented prior to the index hospitalization (but no prior family or behavioral history documentation), they would be labeled as having prior medical history and SDH documentation but not family or behavioral history documentation. These alternative measures allowed us to explore whether having prior history data in the EHR was associated with engagement during an encounter.

Finally, to evaluate if the presence of a previously documented social need was associated with SDH data engagement, we created measures of previously documented social needs for three types of social risk factors signifying whether the risk was present or absent: financial resource strain, food insecurity, and transportation needs.

Statistical analyses

We constructed Kaplan–Meier survival tables and computed log-rank statistics to assess time to 30-day, 90-day, and 1-year readmissions by SDH data engagement. We assessed readmission risk using Cox proportional hazard regression models adjusted for patient demographic and hospitalization characteristics. We generated log–log plots of survival to ensure that our models met the assumption of proportional hazards. We computed point estimates using a linear combination of coefficients postestimation test to characterize the differences in magnitude between the coefficients for each of our history measures.

Next, we focused only on our primary measure of SDH data engagement and identified patient demographic and hospitalization characteristics associated with SDH history data engagement versus no engagement using multivariable logistic regression. Finally, we measured the proportion of hospitalizations with History Activity data engagement for each domain: Medical, Family, Behavioral, and SDH—both for our primary and alternative measures.

All analyses were performed using Stata version 17 (StataCorp). This study was approved by UCSF's IRB (# 20-30268).

RESULTS

Our study sample included 69 921 unique patients and 137 330 inpatient hospitalizations (Table 2). Patients had an average length of stay of 6.93 days.

Readmissions associated with SDH data engagement

In Kaplan–Meier curves, we observe a lower likelihood of 30-day, 90-day, and 1-year readmission among encounters with SDH date engagement relative to encounters without (1-year readmission risk shown in Figure 1). Similarly, in a log-rank test of the null hypothesis of having no difference in survival between patients with no SDH data engagement and those with SDH data engagement, we reject the null hypothesis and observe significant differences in survival ($\chi^2 = 607.62$, $P < .001$).

In patient-level Cox regression models adjusted for age, gender, race, ethnicity, insurance type, whether the patient has a UCSF PCP, admission type, and discharge service, we observe that encounters with SDH data engagement had a significantly lower likelihood of 30-day, 90-day, and 1-year readmission relative to encounters without (Table 3). Similarly, we observe a significantly lower likelihood of 30-day, 90-day, and 1-year readmission among encounters with medical, family, and/or behavioral history engagement, relative to those without (Table 3). However, in postestimation tests, we observe significantly larger in magnitude coefficients on our SDH data engagement measures relative to medical and behavioral history data engagement

Table 1. Documentation fields in each history domain

Medical	Family	Behavioral	SDH
• Name of disease/problem • Approximate date of onset • Problem nickname • Who provided the medical history • Surgical history • Pertinent negative history	• Family member ID • Relationship to patient • Date of birth • Age at death • Genetic sex • Adoption status and parents • Fertility status • Family member's medical history	• Smoking/Tobacco use • Alcohol use • Illicit drug use • Sexual activity	• Marital status and number of children • Employment • Education attainment • Financial resource strain • Food insecurity • Transportation needs

SDH: social determinants of health.

Table 2. Inpatient hospitalization characteristics (February 1, 2018–April 30, 2021, n = 137 330)

|	N	%
Admission type		
Elective	48 654	35.43
Emergency	47 485	34.58
Urgent	39 835	29.01
Trauma center	191	0.14
Newborn	1165	0.85
Discharge service		
Medical	44 458	32.37
Surgical	52 149	37.97
Subspecialty	40 691	29.63
Other	32	0.02
Had UCSF primary care physician	33 548	24.43
Age on admission (mean in years [SD])	48.2 (23.8)	
Gender		
Female	73 398	53.45
Male	63 892	46.52
Other/Unknown	40	0.03
Race		
White or Caucasian	68 927	50.19
Black or African American	13 563	9.88
Asian	21 852	15.9
Native Hawaiian or Other Pacific Islander	1698	1.24
American Indian or Alaskan Native	1475	1.07
Other	27 490	20.02
Unknown/Declined	2325	1.69
Ethnicity		
Hispanic or Latine	25 869	18.84
Not Hispanic or Latine	108 924	79.32
Unknown/Declined	2537	1.85
Insurance type		
Private	43 637	31.78
Medicare	53 077	38.65
Medicaid/Medical	34 818	25.35
Self-pay	4568	3.33
Other	1230	0.90
Length of stay (mean in days [SD])	6.93 (13.0)	

UCSF: University of California, San Francisco.
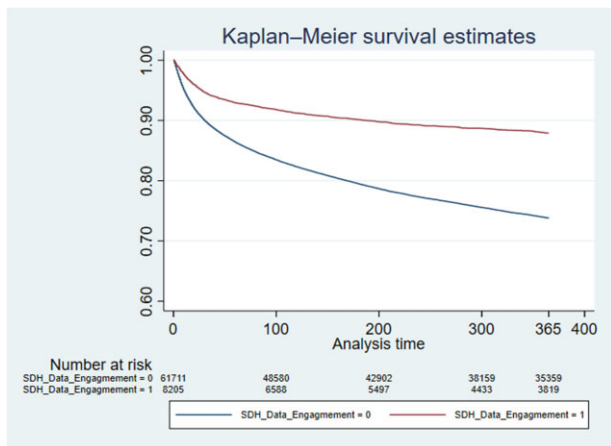
Figure 1. Kaplan–Meier survival estimates for 1 year readmission given SDH data engagement: UCSF Health (February 1, 2018–April 30, 2021, n = 69 916). SDH: social determinants of health; UCSF: University of California, San Francisco.

Table 3. Patient-level Cox Regression Models predicting readmission: UCSF Health (hazard ratios, n = 69 916, Adjusted for patient and encounter characteristics)[a]

	30 days	90 days	1 year
Encounter had SDH data engagement (ref: No SDH Data Engagement)	0.751***	0.759***	0.772***
Encounter had medical history engagement (ref: No Medical Hx Engagement)	0.682***	0.673***	0.665***
Encounter had family history engagement (ref: No Family Hx Engagement)	0.836***	0.836***	0.853***
Encounter had behavioral history engagement (ref: No Behavioral Engagement)	0.517***	0.504***	0.497***

SDH: social determinants of health.
[a]Adjusted for age, gender, race, ethnicity, insurance status, has UCSF PCP, admission type, discharge service, and documented financial resource strain, food insecurity, or transportation need.
***$P < .001$.

coefficients. Patients with previously documented financial resource strain had a significantly lower likelihood of 30-day, 90-day, and 1 year readmission relative to those without, though neither previous documentation of food insecurity nor transportation need were significantly associated with readmission risk compared to those without these social risk factors (Figure 2).

Characteristics associated with SDH data engagement during inpatient hospitalization

Among all hospitalizations, older patients had lower odds of SDH data engagement during the hospitalization relative to younger patients (Table 4). Non-Hispanic Black or African American and Hispanic patients had lower odds of SDH data engagement during hospitalizations relative to Non-Hispanic White patients and Hispanic or Latine patients. Relative to privately insured patients, Medicare patients and those who self-pay for care had lower odds of SDH data engagement. Emergency, urgent care, trauma center, and newborn admissions had higher odds of SDH data engagement relative to elective admissions, while surgical and subspecialty discharges had lower odds of SDH data engagement relative to medical discharges. Finally, patients with previously documented financial resource strain, food insecurity, and transportation needs in the History Activity had a significantly higher likelihood of SDH data engagement than those without.

Comparing levels of engagement for medical, family, behavioral, and SDH history data

We observed substantial variation across our engagement measures, with behavioral and medical history featuring higher levels of engagement than family and SDH measures. Specifically, behavioral and medical history fields had the highest level of engagement during hospitalization (17.77% and 12.48% of hospitalizations, respectively, Figure 3). Family history subsequently had a lower level of engagement (14.42% of hospitalizations). SDH had the lowest level of engagement, during 8.37% of hospitalizations.

For our alternative measures that were limited to encounters with documentation prior to the index hospitalization, a larger proportion of hospitalizations had data engagement during the index
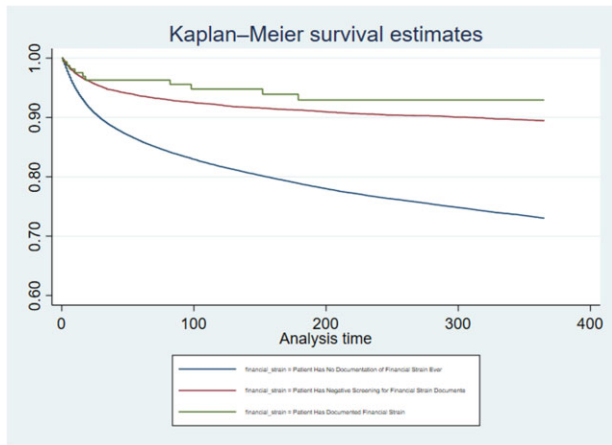
Figure 2. Kaplan–Meier survival estimates for 1 year readmission given documentation of financial resource strain: UCSF Health (February 1, 2018–April 30, 2021, n = 69 916). UCSF: University of California, San Francisco.

hospitalization than observed in our full sample. SDH data engagement was the highest: 72.60% of 15 837 hospitalizations with prior SDH data available (Figure 4). This was followed by behavioral history (54.81% of 76 411 hospitalizations with prior behavioral history data available), medical (34.79% of 82 380 hospitalizations with prior medical history data available), and family (34.75% of 56 971 hospitalizations with prior family history data available).

Discussion

Using a novel quantitative measure of SDH data engagement to measure clinicians' interaction with structured SDH documentation, we found that SDH data engagement was associated with a lower probability of hospital readmission. This emphasizes the importance of SDH data accessibility especially as SDH documentation tools are increasingly implemented in EHRs. Our measures of History Activity engagement may serve as a proxy for use of different types of clinical information, ultimately in service of measuring clinician cognitive processes and behaviors related to using these data. For example, the observed reduction in readmission risk among patients with SDH data engagement may represent clinicians who have the capacity or resources to identify and address patients' social needs, and indeed, we observe that patients with previously documented financial resource strain had a significantly lower likelihood of readmission. While further work is needed to explore *how* clinicians are engaging with SDH data, our findings highlight that any SDH data engagement is relevant to readmission.

We also observed that clinicians engaged with SDH data at lower levels than medical, family, and behavioral history structured data fields. While clinician engagement with historical EHR data is known to be low,[26] our study adds to this by showing frequently clinicians engage with SDH data relative to other types of medical history data. While we found engagement to be low across all four domains, SDH data engagement was notably lower, as we observed that clinicians engaged with SDH historical data in fewer than 1-in-10 hospitalizations. Several reasons may explain low *relative* levels of SDH data engagement. First, the different history domains are presented on separate pages in the Epic user interface, and thus clinicians may not be aware of SDH data documentation capabilities in their EHR, despite availability in most vendors' EHR products.[30] Additionally, clinicians may have limited training related to SDH

Table 4. Inpatient hospitalization-level logistic regression models predicting SDH data engagement (odds ratios, n = 137 330)

	SDH data engagement
Age	
<26	1
≥26 and age <50	0.470***
≥50 and age <65	0.456***
≥65	0.636***
Gender	
Female	1
Male	1.030
Other/Unknown	1.324
Race	
White or Caucasian	1
Black or African American	0.905**
Asian	1.007
Native Hawaiian or Other Pacific Islander	1.224*
American Indian or Alaskan Native	1.023
Other	1.177***
Unknown/Declined	1.405***
Ethnicity	
Not Hispanic or Latine	1
Hispanic or Latine	0.885***
Unknown/Declined	1.353***
Insurance	
Private	1
Medicare	0.687***
Medicaid/Medical	0.979
Self-pay	0.885*
Other	1.124
Has UCSF PCP	0.682***
Admission source	
Elective	1
Emergency	2.451***
Urgent	1.930***
Trauma center	7.806***
Newborn	1.896***
Discharge service	
Medical	1
Surgical	0.673***
Subspecialty	0.712***
Other	1.121
Patient had documented financial resource strain	5.418***
Patient had documented food insecurity	1.626*
Patient had documented transportation need	1.860*

SDH: social determinants of health; UCSF PCP: University of California, San Francisco primary care physician.
*P < .05.
**P < .01.
***P < .001.

screening and social care,[31,32] and current clinical workflows may lack sufficient time, resources, or staffing to address patients' social needs.[33,34]

Conversely, in instances in which each respective history domain had data documented before the hospitalization, clinicians engaged with SDH data more often than they did with medical, family, and behavioral history fields. This finding may indicate that clinicians view SDH data to be important to review. Furthermore, the observed higher level of SDH data engagement among those hospitalizations with previously documented SDH data, especially when certain social needs are present, may be partially explained by the Epic Social Determinants of Health Wheel and Sidebar widgets,
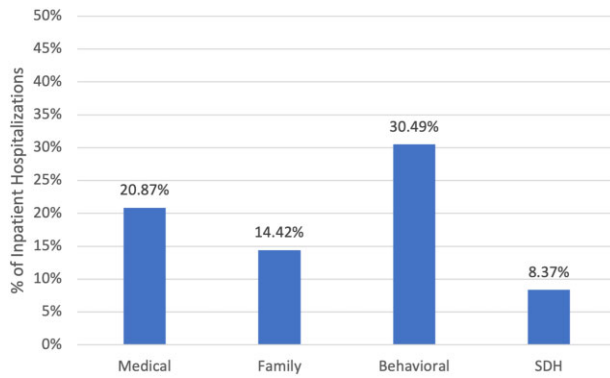
Figure 3. Inpatient hospitalizations with medical, family, behavioral, and SDH history engagement: UCSF Health (February 1, 2018–April 30, 2021, $n = 137\ 330$). SDH: social determinants of health; UCSF: University of California, San Francisco.
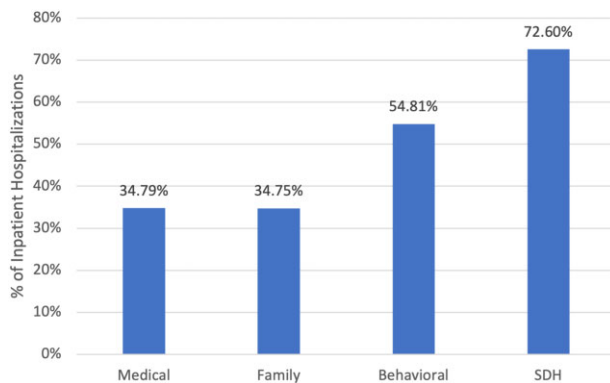

Figure 4. Inpatient hospitalizations with medical, family, behavioral, and SDH history engagement limited to those with prior documentation: UCSF Health (February 1, 2018–April 30, 2021, $n = 137\ 330$). SDH: social determinants of health; UCSF: University of California, San Francisco.

which display icons in green, yellow, and red corresponding to social risk from previously documented data. As a result, clinicians may have had additional prompting to engage with SDH data for patients with previously documented SDH data may be due to this visual display of social risk, potentially suggesting that interventions focused on the EHR user interface may create opportunities to improve SDH data engagement. However, it is also possible that our observation of high levels of engagement with previously collected SDH data can be attributed to patient populations whose clinicians are more motivated to engage with these data, such as patients with complex social needs or chronic medical conditions.

We observed disparities in engagement with SDH data across demographic groups, with older patients; Black, African American, Hispanic, and Latine patients; and publicly insured patients having lower odds of SDH data engagement during hospitalization. This may contribute to inequities in readmissions given our finding of the association between SDH data engagement and readmission risk. Demographic groups with lower relative rates of clinician SDH data engagement, possibly due to conscious or unconscious bias on behalf of clinicians,[35] may not benefit from referrals to community resources and/or receive medical care adjusted to account for social circumstances.[10,27] Given known social disparities among older patients[36] and those identifying as Black or African American and Hispanic or Latine,[37] it is especially important that clinicians engage

with SDH data to provide beneficial social care resources when necessary. These findings suggest that informatics can help us identify disparities among certain patient populations and clinics. Furthermore, informatics may provide opportunities for interventions to encourage SDH data engagement in those demographic groups with historically less SDH data engagement and who may be subject to health disparities, such as via CDS tools and user interface adaptations.

Similarly, we observed the differences in odds of engagement with SDH data across admissions sources and discharge service areas. Higher observed odds of SDH data engagement in admissions from emergency departments, urgent care, and trauma centers relative to elective admissions may suggest that engagement is more likely among patients with critical acute needs and who may be particularly vulnerable based on social context at discharge. Further research should explore effective strategies for addressing the needs of these patients. Additionally, lower observed odds of SDH data engagement among surgical and subspecialty hospitalizations are likely to reflect the current capability of these specialties to provide social risk-informed or targeted care. These specialties may offer untapped opportunities for informatics interventions to expand engagement with SDH data. For example, evidence linking SDH to worsened postoperative outcomes[38–41] has motivated calls for surgical practices to begin screening for and addressing social needs prior to surgical procedures to improve outcomes such as length of stay.[41,42] Furthermore, in clinics with limited opportunities for training or historically less engagement in social care, informatics tools such as CDS and CRRPs may allow providers to offer referral resources.[43] Finally, our observation that patients with previously documented financial resource strain, food insecurity, and transportation needs had a significantly higher likelihood of SDH data engagement may suggest that clinicians are interested to know about and use social risk factor data to address social needs or to tailor clinical decisions accordingly.

In a broader context, our results can inform efforts to advance social care quality measures. Such measures are under consideration and development at several agencies, including NCQA,[44–46] CMS,[47,48] and the Joint Commission.[49–51] While currently proposed measures may focus on screening and referrals,[46] the creation of measures related to SDH data engagement, a critical step in between screening and referrals representing clinicians' intention to inform themselves about patients' social needs, may offer additional context about the extent to which clinicians across an institution are interacting with SDH data, which in turn may be used to inform the design of interventions to promote social care. Quality measures may make use of discrete SDH data for measurement and reporting, though low rates of SDH data engagement would limit the ability to measure how often screening and social care interventions are in use, especially during encounters in which no SDH data engagement occurs. Furthermore, variation in SDH screening and data engagement across patient populations and clinical settings may further limit the extent to which discrete SDH data used in quality measures capture the true extent of screening and social care provided to patients. As a result, understanding relative levels of engagement with the SDH data that are reported will be important to contextualizing these data as quality measures are implemented.

Limitations

Several key limitations of this study should be considered. First, our study only represents engagement with structured data elements

contained within the History Activity. As clinicians are likely discussing social history data with patients and documenting it in other areas of the chart such as free-text clinical notes or ICD-10 Z codes, our data do not attempt to capture all the modalities in which clinicians are both discussing and documenting SDH. Indeed, prior work has shown that SDH information is more readily documented in free note text as opposed to structured data.[52] Additionally, SDH data captured in the History Activity do not represent the entirety of SDH data in the EHR, and clinicians may engage with other sources of SDH data in other parts of the EHR, such as patient self-reported SDH data captured in the patient portal. As a result, our measures reflect only clinician engagement with History Activity SDH data, and engagement with other SDH data may be occurring that is not measured here. Furthermore, EHR tools to mark data elements as reviewed may be used inconsistently, and in UCSF's version of Epic, it can indicate the review of multiple history items, limiting our ability to identify which specific fields were reviewed. Engagement with SDH data may also be difficult to measure because other members of the healthcare team, such as case managers or social workers, may perform follow-up which may not be reflected in our measures. Moreover, our measures of engagement may not reflect clinicians' review of the Epic Social Determinants of Health Wheel and Sidebar widgets, which we are unable to measure with available data. Additionally, we are unable to capture whether clinicians view the SDH data on the page and simply do not click the "Mark as Reviewed" button. Our estimates of SDH (and all other domain) engagement are likely underestimates of actually viewing the information. Finally, our measures represent engagement with history data in only one institution's instance of the History Activity, which may not match those in other facilities. However, UCSF uses a widely adopted EHR and has both patient populations and clinician populations that likely generalizes to other inpatient settings in the United States.

CONCLUSION

We found that metadata measurement of clinician engagement with EHR SDH data is a strong predictor of hospital readmission. However, overall levels of SDH data engagement—including both data documentation and review—are lower than those of common medical, behavioral, and family history data. When SDH data fields were previously documented we observed higher levels of subsequent SDH data engagement, suggesting that SDH data are valuable and indicating the need for workflows that encourage both the capture and use of structured SDH data. Informatics interventions, including CDS and EHR user interfaces, should emphasize equity considerations to address observed disparities in SDH data engagement across patient demographic groups. More broadly, these efforts will help facilitate the utilization of social services referrals and support emerging quality measurement efforts.

AUTHOR CONTRIBUTIONS

BI contributed to the conception and design of this study, data collection, data analysis and interpretation, drafting of the article, critical revision of the article, and final approval of the version to be published. JA-M, LG, and MP contributed to the conception and design of this study, data interpretation, drafting of the article, critical revision of the article, and final approval of the version to be published. BI, JA-M, LG, and MP agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

SUPPLEMENTARY MATERIAL

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

CONFLICT OF INTEREST STATEMENT

None declared.

DATA AVAILABILITY

The data underlying this article cannot be shared publicly in order to protect the privacy of individuals represented in the dataset.

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