American Journal of
Preventive Medicine

RESEARCH ARTICLE

Impact of Risk Stratification on Referrals and Uptake of Wraparound Services That Address Social Determinants: A Stepped Wedged Trial

Joshua R. Vest, PhD, MPH,[1,2] Nir Menachemi, PhD, MPH,[1,2] Shaun J. Grannis, MD, MS,[2,3] Jennifer L. Ferrell, MSN, RN,[4] Suranga N. Kasthurirathne, PhD,[2,5] Ying Zhang, PhD,[6] Yan Tong, PhD, MS,[6] Paul K. Halverson, DrPH[1,2,3]

Introduction: Social determinants of health are critical drivers of health status and cost, but are infrequently screened or addressed in primary care settings. Systematic approaches to identifying individuals with unmet social determinants needs could better support practice workflows and linkages of patients to services. A pilot study examined the effect of a risk-stratification tool on referrals to services that address social determinants in an urban safety-net population.

Methods: An intervention that risk stratified patients according to the need for wraparound was evaluated in a stepped wedge design (i.e., phased implementation at the clinic level during 2017). Staff at nine federally qualified health centers received a daily report predicting patients' needs for social worker, dietitian, behavioral health, and other wraparound services (categorized as low, rising, or high risk). Outcomes included referrals and uptake of appointments to wraparound services.

Results: Among 238,087 encounters, providing clinic staff with risk-stratification scores increased the odds that a patient would be referred to a social worker. For patients categorized as high risk, the odds of a social work referral was 65% higher than controls and similar patients, but lower effect sizes were observed for individuals categorized with rising and low risk. Among referred patients, the intervention was generally associated with increased odds of kept appointments.

Conclusions: This study provided preliminary evidence that risk-stratification interventions to identify patients in need of wraparound services to address social determinants can increase referrals and uptake of services that may address social drivers of disease burden.
Am J Prev Med 2019;56(4):e125−e133.

INTRODUCTION

Social determinants of health include the behaviors, social situations, socioeconomic conditions, and physical and policy environments that contribute to health and well-being.[1,2] These factors increase patient complexity and complicate the delivery of care,[3,4] and are associated with increased services utilization and poorer health outcomes.[5,6] Providers and payers are increasingly becoming more attentive to the challenges and costs posed by patients' social determinants.[7,8] For example, health systems are partnering with community organizations to offer social services[9] and the American Medical Association endorses physician training in social determinants.[10]

From the [1]Department of Health Policy and Management, Richard M. Fairbanks School of Public Health, Indiana University, Indianapolis, Indiana; [2]Regenstrief Institute, Indianapolis, Indiana; [3]Department of Family Medicine, School of Medicine, Indiana University, Indianapolis, Indiana; [4]Eskenazi Health, Indianapolis, Indiana; [5]Department of Epidemiology, Richard M. Fairbanks School of Public Health, Indiana University, Indianapolis, Indiana; and [6]Department of Biostatistics, School of Medicine and Richard M. Fairbanks School of Public Health, Indiana University, Indianapolis, Indiana

Address correspondence to: Joshua R. Vest, PhD, MPH, Department of Health Policy and Management, Richard M. Fairbanks School of Public Health, Indiana University, 1050 Wishard Boulevard, RG 5124, Indianapolis IN 46202. E-mail: joshvest@iu.edu.

0749-3797/$36.00
https://doi.org/10.1016/j.amepre.2018.11.009

Additionally, screening for and addressing the social determinants of health are critical components of the Center for Medicare & Medicaid Services Accountable Health Communities program.[11]

Despite their importance, primary care providers infrequently screen for, assess, or address social determinants because of a combination of factors.[12] Providers may simply lack time[13] or may be insufficiently knowledgeable about social determinants.[14] Even when aware of social factors, providers may have concerns that these determinants cannot be adequately resolved in an office visit.[15] Moreover, practices are hampered by insufficient documentation capability within electronic health records (EHRs).[16] Also, patients may be reluctant to share stigmatizing social information.[17] As a result, patients' needs arising from social determinants are frequently unknown, underestimated, and left unaddressed.[18−20]

Standardized and systematic approaches to identifying those with social needs could better support primary care workflows and the linkage of patients to necessary services.[20−22] One such systematic approach is to leverage risk stratification, or risk prediction, methods to identify patients most in need of intervention.[23] Risk stratification is already widely applied in health care to better understand negative clinical outcomes, including readmissions or death,[23] and population health needs, such as identifying patients requiring care coordination or those that are high cost/high utilizers.[24] Risk stratification makes use of the ever growing amount of available electronic patient data and can incorporate both patient and community contextual information in an effort to inform decision making or to automate processes and orders.[24,25]

This study evaluates the use of automated risk stratification as an approach to better identifying patients with the greatest needs for various wraparound services that can address the social determinants of health. Specifically, the study assesses whether an intervention that risk stratified patients according to need results in increased referrals and uptake of wraparound services provided by social workers, dietitians, behavioral health specialists, and other service providers addressing social issues in a vulnerable, safety-net population. A growing body of research indicates these professionals can be effective in addressing patient needs.[26−28]

METHODS

A stepped wedge design[29] was used to evaluate the impact of automated risk stratification for wraparound services in nine federally qualified health center (FQHC) clinic sites. The intervention was an automated process that provided risk-stratification scores to staff and was introduced in three clinics at a time over a 1-year period in 2017. The intervention's phased introduction in a stepped wedge design had multiple advantages: it facilitated implementation within the study clinics, it allowed for outcome measurement in both pre- and post-intervention phases, and it increased the statistical power for detecting the intervention effect. Risk-stratification scores were based on data available from the FQHC's EHR, the community-based health information exchange, and key neighborhood characteristics pertaining to the patient's ZIP code.

Study Sample

The study sites were the nine primary care clinics at Eskenazi Health, a 315-bed public hospital in Indianapolis, Indiana. Eskenazi Health has offered behavioral health services, dietitian counseling, social work services, respiratory therapy, financial planning, medical-legal partnership assistance, patient navigation, and pharmacist consultation on a co-located basis with primary care. Collectively, these services were labeled as wraparound services (i.e., additional nonmedical services that support the delivery of primary care). Importantly, dedicated staff provided these services in-house, that is, patients were not referred to outside entities for service.

Measures

Leveraging 6 years of patient-level data from the EHR, the local health information exchange, and small-area aggregate socioeconomic and public health indicators, machine learning algorithms identified adult patients who may need a referral to wraparound services.[30] The machine learning algorithms resulted in five output scores: (1) an overall predicted risk score indicating a given patient's probability of needing a referral to any wraparound services, and specific predicted risk scores indicating the potential need for (2) behavioral health services, (3) dietitian counseling, and (4) social work services. A fifth prediction score reflected the need for any other wraparound services (combined because of a small number of observations). The algorithm performed within the useful range of discriminatory ability,[31] with area under the curve values ranging from 70% to 78%.[30] In consultation with providers, patients' predicted risk scores were risk stratified into the following categories: low need (the lowest 80% of scores), rising risk (scores in 80th to 95th percentiles) and high risk (scores in the top 95th percentile of all scores). The percentile distribution was based on historical data on the entire FQHC adult patient population (e.g., a patient with a risk score in the high-risk category had a score >95% of all other adult patients).

The intervention was the delivery of risk-stratification information on a daily basis using an automated batch process. Early each morning, Eskenazi Health submitted listings of adult patients scheduled for primary care appointments. The receipt of this scheduled patient list triggered an automated query of multiple data sets for relevant data elements, which were included in the machine learning algorithm.[30] The result of the process was a text report with patient identifiers and risk-stratification scores and categories, as described here. The resulting report was automatically returned to each clinic before opening hours and was accessible to that clinic's staff on a secure intranet site. The primary anticipated users of the reports were the wraparound service providers and the clinics' population health nurse. The report was intentionally delivered before clinic opening so that staff: (1) had the information before discussion of the day's patients at the daily provider team meetings, and (2) had time to identify any patients for potential wraparound service consultation. The intervention was introduced at the clinic level. Patients without scheduled visits were not included in the risk-stratification report. The study team that included an Eskenazi Health clinician introduced the concept of the risk-stratification report to the clinic staff at regular staff meetings 1 month prior to the clinic going live. Risk-stratification results did not automatically trigger any referrals, viewing the report was not mandated, nor were any patients required to be (or not to be) referred to services based on risk-stratification scores. Providers were not required to specifically engage any risk level or specifically exclude patients in lower risk levels. Therefore, the intervention provided risk-stratification information as another "data point" to include in clinicians' own decision-making processes and workflows.

In June 2017, three clinics went live with the daily reports. At study Month 4, three more clinics went live, and at study Month 6, the remaining three clinics went live. All primary care encounters from January 2017 until each clinic implemented the intervention served as control observations. The primary independent variable measured the clinic intervention status and the risk-stratification categories at the individual encounter level: control period encounter, same-day appointment (i.e., no risk score because unscheduled patient visit), low risk, rising risk, or high risk.

Referral to a wraparound service during a primary care encounter was the primary endpoint of the current study. The secondary endpoint was patient uptake (e.g., whether the referred appointment was kept) of a wraparound service. Results were summarized by dietitian, behavioral health, social work, and all other service referrals combined. The latter category was combined due to a small number of referrals. Referrals and kept appointments for Eskenazi Health's general health and lifestyle management program served as a control outcome. This control outcome was appropriate because, like wraparound services, the program was offered at multiple locations, required a primary care referral, and was not related to a specific clinical condition. This control outcome was not included in the risk-stratification intervention. Control outcomes serve as a check against internal validity threats like the presence of an unmeasured confounding factor or selection bias.[32,33]

Covariates included patient demographics (age, gender, race/ethnicity) and calculated Elixhauser comorbidity scores.[34]

Statistical Analysis

Percentages and means described the study sample. A series of generalized estimating equations for logistic regression models, which account for the repeated measurement of patients, evaluated the impact of the intervention on primary and secondary endpoints. Separate regression models were fit for each outcome. All models were adjusted for patient demographics, comorbidity score, and clinic location. This project was approved by the Indiana University IRB.

RESULTS

The study sample included 238,087 encounters among 57,490 unique patients. Intervention and control encounters differed statistically, but not meaningfully, by age, gender, race-ethnicity, and mean comorbidity scores (Table 1). The mean rate of referrals for wraparound services among control encounters was 9.5%. Rates of referrals for patients in the risk-stratification intervention were higher at 9.8% (p=0.006). Rates of referrals were highest for dietitians. Very infrequently (<1%) did an encounter result in a referral to any of the other wraparound services. About one third of encounters with appointments to a wraparound service kept the appointment (35%). The percentage of encounters with kept appointments among referrals to dietitians, behavioral health, and social workers were higher in the intervention group. The percentage of encounters with referrals to the free general health and wellness program and the proportion of referred patients that kept those appointments did not significantly differ between intervention and control groups.

Overall, providing clinicians with risk-stratification information was not associated with an increase in referrals to wraparound services as a whole (Figure 1). However, the odds that a patient would be referred to social work were higher in intervention periods than in control periods. For the high-risk stratification category, the odds of a social work referral was 65% higher (OR=1.65, 95% CI=1.40, 1.95), 33% higher for the rising-risk stratification category, and 47% higher for the low-risk category. In the intervention clinics, patients with same-day appointment who did not receive risk scores (i.e., those with unscheduled appointments, which were 22.1% of encounters) also had higher odds of a referral to a social worker (OR=1.32, 95% CI=1.12, 1.55). For all other wraparound services (i.e., dietitians, behavioral health, and all others combined), the intervention was not associated with any increases in referrals. For these services, patients with same-day appointments had significantly lower odds of referrals compared with the patients in the control periods. The intervention was not significantly associated with referrals to the general health and wellness program (the control outcome).

Among referred patients, the intervention was generally associated with increased odds of kept appointments (Figure 2). The increased odds of keeping any wraparound service appointment ranged from 48% for the high-risk group, to 29% for rising-risk group, to 39% for the low-risk group. Patients with same-day appointments (i.e., no risk scores) also had increased odds of keeping appointments. Although sample sizes were small, odds of kept appointments were generally higher for dietitians and behavioral health as well. Among social workers, the service that was observed to have increased odds of referrals, risk-stratified patients generally had higher odds of keeping the appointment. The intervention was not associated with keeping appointments for all other service providers and was not significantly

Table 1. Characteristics of Encounters by Intervention and Control Clinic Sites

Variable	Total (N=238,087)	Intervention (*n*=62,254)	Control (*n*=175,833)	*p*-value
Demographics				
Age, years, M (SD)	47.1 (16.1)	47.5 (16.1)	47.0 (16.1)	**<0.0001**
Female, %	70.7	69.6	71.1	**<0.0001**
Race/ethnicity, %				**<0.0001**
White	29.3	30.2	29.0	
Black or African American	48.1	48.2	48.1	
Other	22.6	21.6	22.9	
Hispanic	21.7	20.1	22.2	
Elixhauser score, M (SD)	2.0 (1.8)	2.1 (1.8)	1.9 (1.8)	**<0.0001**
Referrals, %				
Any social determinant of health	9.6	9.8	9.5	**0.0061**
Behavioral health	2.9	3.1	2.8	**0.0007**
Dietitian	5.2	5.0	5.4	**0.0300**
Social worker	1.2	1.6	1.0	**<0.0001**
Other[a]	0.9	0.8	0.9	**0.0080**
General health education program, %	1.1	1.0	1.1	0.3128
Kept appointments,[b] %				
Any social determinant of health	32.1	34.8	31.1	**<0.0001**
Dietitian	33.8	36.6	32.9	**<0.0001**
Behavioral health	28.3	32.5	26.7	**<0.0001**
Social worker	23.5	26.3	21.9	**0.0089**
Other[c]	19.8	16.0	21.0	**0.0161**
General health education program, %	7.3	6.7	7.6	0.4562

Note: Boldface indicates statistical significance ($p<0.05$).
[a]Medical-legal partnership, financial counseling, respiratory therapy, patient navigation, and pharmacist consultation (combined due to small sample sizes).
[b]Among those with referrals for each service.
[c]The general health program required referrals, but was not included in the risk-stratification modeling.

associated with kept appointments to the general health and wellness program (the control outcome).

DISCUSSION

Providing primary care clinic staff with risk-stratification information on patients' need for wraparound services increased referrals to social workers and increased the odds of kept appointments for multiple wraparound service providers that may address social determinants of health. This finding indicates that proactively identifying patients in need of social and other services, using risk stratification derived from machine learning methods, can support improvements in care delivery. The effective and efficient delivery of services that address the social determinants of health will increasingly be a key capability as healthcare organizations assume greater accountability, and financial risk, for assuring patients' health.

This study's automated risk-stratification intervention responds directly to recent calls to increase the systematic screening of social determinants,[21] better leverage electronic data,[35] and transform data into useful information through risk predictions.[22,36] Layering automated risk stratification on to the increased health information technology usage in primary care[37] is an opportunity to improve the identification of, and to address patients' needs stemming from, social determinants.[38] Current research on screening initiatives has revealed a high need for services,[17,18,20] the potential for the practice of screening to change provider and workplace attitudes,[18] and that screening can be an effective tool for identifying those in need of an intervention.[39,40] Automated risk stratification could complement and also enhance efforts to increase the usage of screening questionnaires[41] and the collection of structured social determinants data.[42] Moreover, an automated risk-stratification intervention could help overcome the primary limitation of providers' lack of screening for this information.[12] As a future application, risk stratification and specific, standardized data could be combined into rule-based standing orders or automatic referrals to services within EHRs.[38]

Although the need for wraparound services among patients in this study was high, the intervention did not

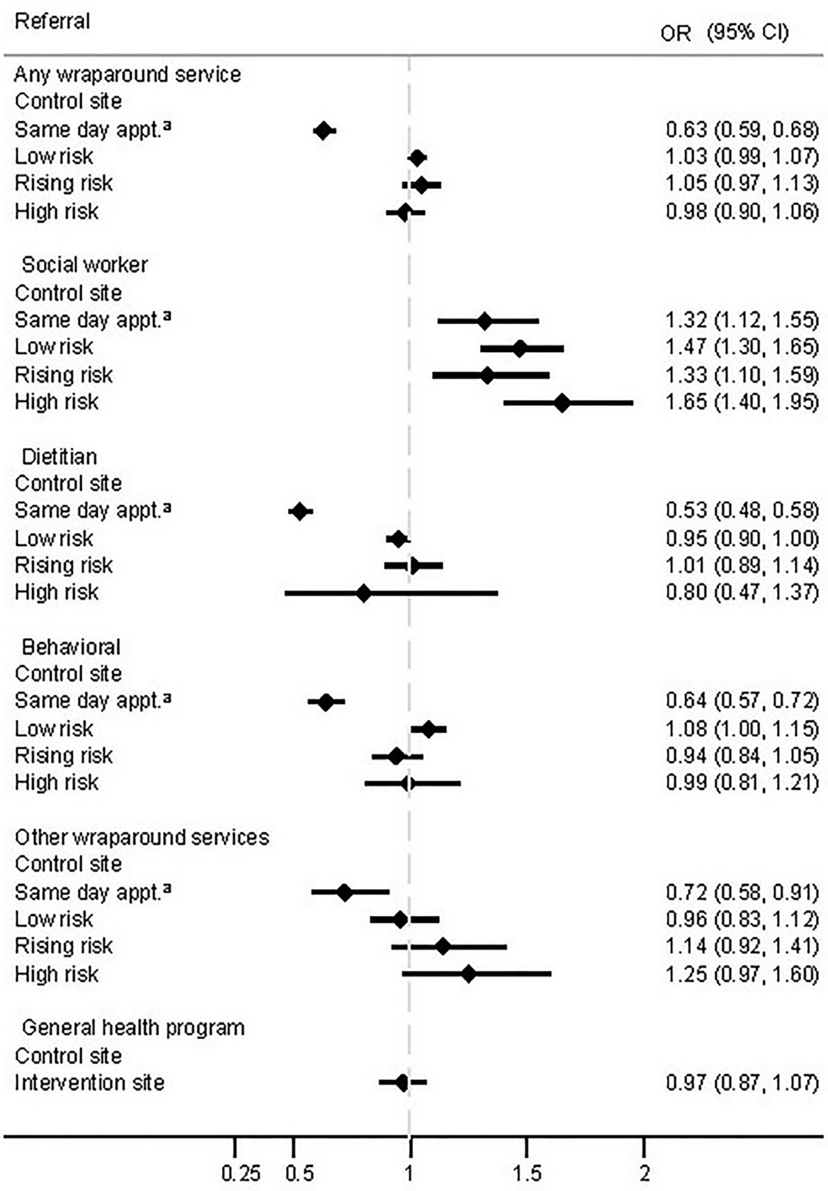

Figure 1. Association between risk stratification and wraparound service referrals.
[a]Same-day appointments at intervention sites did not have risk-stratification scores.

improve referral rates to all services. The lack of any effect on the combined category of legal partnership, financial counseling, respiratory therapy, patient navigation, and pharmacist consultation services may be because of either poor predictive performance or a combination of the very heterogeneous nature and small numbers of these services. Additionally, the absence of any impact on referrals to dietitians was unexpected, but possibly because of a poor match between current clinical practice and the archived data used in the risk-stratification models. Follow-up interviews with dietitians indicated an increasing effort to target services to more narrowly define clinical conditions (e.g., specific HbA1c thresholds or recent discharges with specific diagnoses). Models are being revised to improve performance for these services by including more deterministic rules and by including additional data sources (e.g., 211 calls), biometric measures, and additional clinical indicators. Critically, referrals to social workers increased during the intervention. Social workers can fulfill many roles in addressing patients' social determinants and care needs,[43,44] and social work integration with primary care has been associated with improvements in quality, costs, and health services utilization.[45] Additionally, referrals

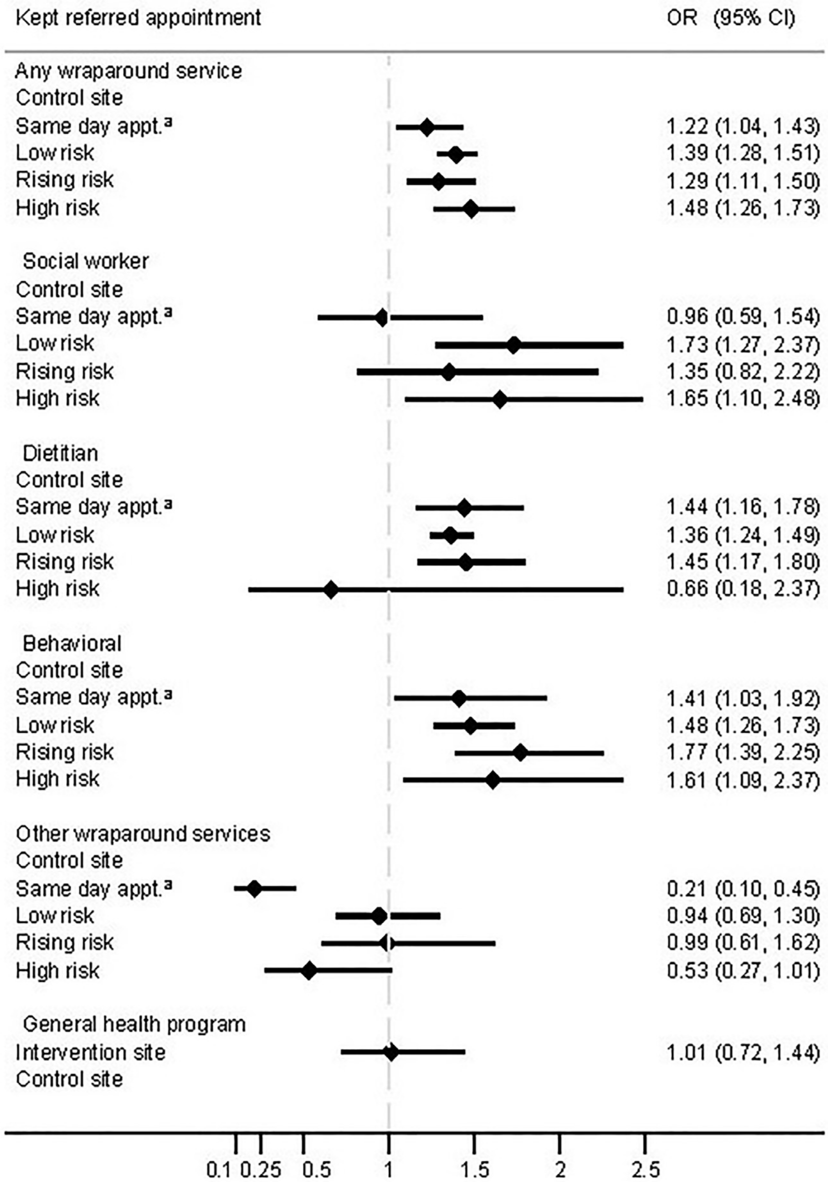

Figure 2. Association between risk stratification and kept social wraparound services appointments.
[a]Same-day appointments at intervention sites did not have risk-stratification scores.

to social workers help address concerns that risk stratification may not adequately consider patient concerns,[46] as social workers at Eskenazi Health undertake additional assessments and screenings with the patients in a patient-centric, collaborative manner.

Given that a sizable proportion of patients referred to wraparound services may not follow-up on the referrals,[40] the positive impact of the intervention on subsequent kept appointments for select services was also promising. Missed appointments, in general, are an inefficient use of organizational resources and increase patient risk for undesirable outcomes.[47]

Despite the increased attentiveness to specific patient needs arising from social issues, primary care organizations face limitations in their ability to independently affect broad change. Although providers may be able to link low-income individuals to government assistance[26] or to medical-legal partnerships that address unsafe living conditions,[27] they are unable to directly address the underlying environmental, economic, societal, and policy issues that exacerbate health. Affecting the broader issues requires partnerships with organizations from other sectors. Public health organizations are a natural partner for such change and have partnered with healthcare organizations to change the physical environment[48] and to identify policies for reform.[49]

This pilot study will be extended by integrating risk-stratification scores into a commercial EHR to create a seamless experience for the end user (no additional log-ins, no leaving the EHR interface) that better fits clinic workflows. This integration moves nearer to real-time risk stratification in order to include same-day appointment patients. Also, the intervention is expanding to all ages, including children. This will require age cohort–specific models, given the children have high social needs as well,[12] and screening for these social needs has proven to be effective.[40] Like the existing approach, the intervention will not require, or prohibit, referrals to any services. Individual providers may still order referrals regardless of risk scores.

Limitations

This pilot study is subject to limitations. First, because all wraparound services were on a co-located basis, findings may not be generalizable to primary care practices that rely on referrals to community partners. Ensuring that patients with social needs actually have viable options for referral is an ongoing concern,[46] but less relevant in this case. Second, other unmeasured factors may have influenced referrals. However, the stepped wedge design should have mitigated against the potential bias from such effects and the use of a control outcome was another check. Third, no statistical difference among the risk-stratification categories was observed, whereas a dose–response relationship could have been expected. The reason could be that the risk-stratification results were not tied to any specific ordering or workflow activity, or that patients in the low-risk category may have an obvious and pressing need missed by the algorithms. Fourth, the hospital's information systems were able to confirm that the reports were delivered, but measuring actual usage was not possible. Additionally, clinic staff may have suggested a referral, but the patient refused, which is a possible outcome of screening.[50] Lastly, the effects of the intervention cannot be separated from the education and training about the intervention. Possibly the intervention created more awareness of social needs and prompted providers to examine their own workflow and activities. However, the control outcome variable suggests there was no increase in referrals or uptake in programs that generally supported health. Additionally, the significant negative association between same-day appointment patients (i.e., no risk-stratification scores because the appointment was unscheduled) and referrals suggests provider workflows did not change to become more attentive to social needs overall. Established clinic workflows tended to focus on scheduled patients for wraparound services referrals.

CONCLUSIONS

An automated intervention that risk-stratified patients in need of wraparound services in an urban, safety-net, adult patient population resulted in increased referrals to social workers and more kept appointments. This pilot study suggests automated risk stratification may be an approach to support healthcare organization's efforts to better address patients' social determinants of health needs.

ACKNOWLEDGMENTS

The authors thank the Regenstrief Data Core, Eskenazi Health, and Amber Blackmon.

This work was supported by the Robert Wood Johnson Foundation through the Systems for Action National Coordinating Center, ID 73485.

No financial disclosures were reported by the authors of this paper.

REFERENCES

1. Braveman P, Egerter S, Williams DR. The social determinants of health: coming of age. *Annu Rev Public Health.* 2011;32:381–398. https://doi.org/10.1146/annurev-publhealth-031210-101218.
2. Marmot M, Friel S, Bell R, Houweling TA, Taylor S. Closing the gap in a generation: health equity through action on the social determinants of health. *Lancet.* 2008;372(9650):1661–1669. https://doi.org/10.1016/S0140-6736(08)61690-6.
3. Fiscella K, Epstein RM. So much to do, so little time: care for the socially disadvantaged and the 15-minute visit. *Arch Intern Med.* 2008;168(17):1843–1852. https://doi.org/10.1001/archinte.168.17.1843.
4. Grant RW, Ashburner JM, Hong CS, Chang Y, Barry MJ, Atlas SJ. Defining patient complexity from the primary care physician's perspective: a cohort study. *Ann Intern Med.* 2011;155(12):797–804. https://doi.org/10.7326/0003-4819-155-12-201112200-00001.
5. Fitzpatrick T, Rosella LC, Calzavara A, et al. Looking beyond income and education: socioeconomic status gradients among future high-cost users of health care. *Am J Prev Med.* 2015;49(2):161–171. https://doi.org/10.1016/j.amepre.2015.02.018.
6. Calvillo-King L, Arnold D, Eubank KJ, et al. Impact of social factors on risk of readmission or mortality in pneumonia and heart failure: systematic review. *J Gen Intern Med.* 2013;28(2):269–282. https://doi.org/10.1007/s11606-012-2235-x.
7. Lee J, Korba C. Social determinants of health: how are hospitals and health systems investing in and addressing social needs? www2.deloitte.com/us/en/pages/life-sciences-and-health-care/articles/addressing-social-determinants-of-health-hospitals-survey.html. Accessed November 12, 2018, Published 2017.
8. Cordier T, Song Y, Cambon J, et al. A bold goal: more healthy days through improved community health. *Popul Health Manag.* 2018;21(3):202–208. https://doi.org/10.1089/pop.2017.0142.
9. Amarashingham R, Xie B, Karam A, Nguyen N, Kapoor B. Using community partnerships to integrate health and social services for high-need, high-cost patients. *Issue Brief (Commonw Fund).* 2018;2018:1–11. www.commonwealthfund.org/sites/default/files/documents/_media_files_publications_issue_brief_2018_jan_amarasingham_integrating_health_social_services_high_need_high_cost_ib.pdf. Accessed November 12, 2018.
10. American Medical Association. Policy Furthers AMA's Efforts to Create Medical School of the Future. www.ama-assn.org/policy-furthers-ama-s-efforts-create-medical-school-future. Accessed April 2, 2018, Published 2017.

11. Alley DE, Asomugha CN, Conway PH, Sanghavi DM. Accountable health communities—addressing social needs through Medicare and Medicaid. *N Engl J Med.* 2016;374(1):8–11. https://doi.org/10.1056/NEJMp1512532.
12. Garg A, Butz AM, Dworkin PH, Lewis RA, Serwint JR. Screening for basic social needs at a medical home for low-income children. *Clin Pediatr (Phila).* 2009;48(1):32–36. https://doi.org/10.1177/0009922808320602.
13. Solberg LI. Theory vs practice: should primary care practice take on social determinants of health now? No. *Ann Fam Med.* 2016;14(2):102–103. https://doi.org/10.1370/afm.1918.
14. Klein MD, Kahn RS, Baker RC, Fink EE, Parrish DS, White DC. Training in social determinants of health in primary care: does it change resident behavior? *Acad Pediatr.* 2011;11(5):387–393. https://doi.org/10.1016/j.acap.2011.04.004.
15. Behforouz HL, Drain PK, Rhatigan JJ. Rethinking the social history. *N Engl J Med.* 2014;371(14):1277–1279. https://doi.org/10.1056/NEJMp1404846.
16. Senteio C, Veinot T, Adler-Milstein J, Richardson C. Physicians' perceptions of the impact of the EHR on the collection and retrieval of psychosocial information in outpatient diabetes care. *Int J Med Inform.* 2018;113(January):9–16. https://doi.org/10.1016/j.ijmedinf.2018.02.003.
17. Pinto AD, Glattstein-Young G, Mohamed A, Bloch G, Leung F-H, Glazier RH. Building a foundation to reduce health inequities: routine collection of sociodemographic data in primary care. *J Am Board Fam Med.* 2016;29(3):348–355. https://doi.org/10.3122/jabfm.2016.03.150280.
18. Page-Reeves J, Kaufman W, Bleecker M, et al. Addressing social determinants of health in a clinic setting: the WellRx Pilot in Albuquerque, New Mexico. *J Am Board Fam Med.* 2016;29(3):414–418. https://doi.org/10.3122/jabfm.2016.03.150272.
19. Bikson K, McGuire J, Blue-Howells J, Seldin-Sommer L. Psychosocial problems in primary care: patient and provider perceptions. *Soc Work Health Care.* 2009;48(8):736–749. https://doi.org/10.1080/00981380902929057.
20. Lewis JH, Whelihan K, Navarro I, et al. Community health center provider ability to identify, treat and account for the social determinants of health: a card study. *BMC Fam Pract.* 2016;17(1):121. https://doi.org/10.1186/s12875-016-0526-8.
21. Garg A, Jack B, Zuckerman B. Addressing the social determinants of health within the patient-centered medical home. *JAMA.* 2013;309(19):2001. https://doi.org/10.1001/jama.2013.1471.
22. DeVoe JE, Bazemore AW, Cottrell EK, et al. Perspectives in primary care: a conceptual framework and path for integrating social determinants of health into primary care practice. *Ann Fam Med.* 2016;14(2):104–108. https://doi.org/10.1370/afm.1903.
23. Cousins MS, Shickle LM, Bander JA. An introduction to predictive modeling for disease management risk stratification. *Dis Manag.* 2002;5(3):157–167. https://doi.org/10.1089/109350702760301448.
24. Vuik SI, Mayer EK, Darzi A. Patient segmentation analysis offers significant benefits for integrated care and support. *Health Aff (Millwood).* 2016;35(5):769–775. https://doi.org/10.1377/hlthaff.2015.1311.
25. Bates DW, Saria S, Ohno-Machado L, Shah A, Escobar G. Big data in health care: using analytics to identify and manage high-risk and high-cost patients. *Health Aff (Millwood).* 2014;33(7):1123–1131. https://doi.org/10.1377/hlthaff.2014.0041.
26. Pinto AD, Bloch G. Framework for building primary care capacity to address the social determinants of health. *Can Fam Physician.* 2017;63(11):e476–e482. www.ncbi.nlm.nih.gov/pubmed/29138172. Accessed August 16, 2018.
27. Sandel M, Hansen M, Kahn R, et al. Medical-legal partnerships: transforming primary care by addressing the legal needs of vulnerable populations. *Health Aff (Millwood).* 2010;29(9):1697–1705. https://doi.org/10.1377/hlthaff.2010.0038.
28. Mani J, Franklin L, Pall H. Impact of pre-procedure interventions on no-show rate in pediatric endoscopy. *Child.* 2015;2(1):89–97. https://doi.org/10.3390/children2010089.
29. Hemming K, Haines TP, Chilton PJ, Girling AJ, Lilford RJ. The stepped wedge cluster randomised trial: rationale, design, analysis, and reporting. *BMJ.* 2015;350:h391. https://doi.org/10.1136/bmj.h391.
30. Kasthurirathne SN, Vest JR, Menachemi N, Halverson PK, Grannis SJ. Assessing the capacity of social determinants of health data to augment predictive models identifying patients in need of wraparound social services. *J Am Med Inform Assoc.* 2018;25(1):47–53. https://doi.org/10.1093/jamia/ocx130.
31. Swets JA. Measuring the accuracy of diagnostic systems. *Science.* 1988;240(4857):1285–1293. https://doi.org/10.1126/science.3287615.
32. Dusetzina SB, Brookhart MA, Maciejewski ML. Control outcomes and exposures for improving internal validity of nonrandomized studies. *Health Serv Res.* 2015;50(5):1432–1451. https://doi.org/10.1111/1475-6773.12279.
33. Shaddish WR, Cook TD, Campbell DT. *Experimental and Quasi-Experimental Designs for Generalized Causal Inference.* Boston, MA: Houghton Mifflin Company; 2002.
34. Elixhauser A, Steiner C, Harris DR, Coffey RM. Comorbidity measures for use with administrative data. *Med Care.* 1998;36(1):8–27. https://doi.org/10.1097/00005650-199801000-00004.
35. Gottlieb L, Sandel M, Adler NE. Collecting and applying data on social determinants of health in health care settings. *JAMA Intern Med.* 2013;173(11):1017. https://doi.org/10.1001/jamainternmed.2013.560.
36. Institute of Medicine. *Capturing Social and Behavioral Domains in Electronic Health Records: Phase 2.* Washington, DC: National Academies Press; 2014. https://doi.org/10.17226/18951.
37. Furukawa MF, King J, Patel V, Hsiao C-J, Adler-Milstein J, Jha AK. Despite substantial progress in EHR adoption, health information exchange and patient engagement remain low in office settings. *Health Aff (Millwood).* 2014;33(9):1672–1679. https://doi.org/10.1377/hlthaff.2014.0445.
38. Gottlieb LM, Tirozzi KJ, Manchanda R, Burns AR, Sandel MT. Moving electronic medical records upstream: incorporating social determinants of health. *Am J Prev Med.* 2015;48(2):215–218. https://doi.org/10.1016/j.amepre.2014.07.009.
39. Garg A, Toy S, Tripodis Y, Silverstein M, Freeman E. Addressing social determinants of health at well child care visits: a cluster RCT. *Pediatrics.* 2015;135(2):e296–e304. https://doi.org/10.1542/peds.2014-2888.
40. Gottlieb LM, Hessler D, Long D, et al. Effects of social needs screening and in-person service navigation on child health: a randomized clinical trial. *JAMA Pediatr.* 2016;170(11):e162521. https://doi.org/10.1001/jamapediatrics.2016.2521.
41. Estabrooks PA, Boyle M, Emmons KM, et al. Harmonized patient-reported data elements in the electronic health record: supporting meaningful use by primary care action on health behaviors and key psychosocial factors. *J Am Med Inform Assoc.* 2012;19(4):575–582. https://doi.org/10.1136/amiajnl-2011-000576.
42. Institute of Medicine. *Capturing Social and Behavioral Domains in Electronic Health Records: Phase 1.* Washington, DC: The National Academies Press; 2014. https://doi.org/10.17226/18709.
43. Stanhope V, Videka L, Thorning H, McKay M. Moving toward integrated health: an opportunity for social work. *Soc Work Health Care.* 2015;54(5):383–407. https://doi.org/10.1080/00981389.2015.1025122.
44. Leach B, Morgan P, Strand de Oliveira J, Hull S, Østbye T, Everett C. Primary care multidisciplinary teams in practice: a qualitative study. *BMC Fam Pract.* 2017;18(1):115. https://doi.org/10.1186/s12875-017-0701-6.
45. Sommers LS, Marton KI, Barbaccia JC, Randolph J. Physician, nurse, and social worker collaboration in primary care for chronically ill seniors. *Arch Intern Med.* 2000;160(12):1825. https://doi.org/10.1001/archinte.160.12.1825.
46. Garg A, Boynton-Jarrett R, Dworkin PH. Avoiding the unintended consequences of screening for social determinants of health. *JAMA.* 2016;316(8):813–814. https://doi.org/10.1001/jama.2016.9282.

47. Nuti LA, Lawley M, Turkcan A, et al. No-shows to primary care appointments: subsequent acute care utilization among diabetic patients. *BMC Health Serv Res.* 2012;12:304. https://doi.org/10.1186/1472-6963-12-304.
48. Litt J, Reed H, Zieff SG, et al. Advancing environmental and policy change through active living collaboratives. *J Public Heal Manag Pract.* 2013;19 (suppl 1):S49–S57. https://doi.org/10.1097/PHH.0b013e3182848056.
49. Vest JR, Caine V, Harris LE, Watson DP, Menachemi N, Halverson P. Fostering local health department and health system collaboration through case conferences for at-risk and vulnerable populations. *Am J Public Health.* 2018;108(5):649–651. https://doi.org/10.2105/AJPH.2018.304345.
50. Gold R, Cottrell E, Bunce A, et al. Developing electronic health record (EHR) strategies related to health center patients' social determinants of health. *J Am Board Fam Med.* 2017;30(4):428–447. https://doi.org/10.3122/jabfm.2017.04.170046.