Using Applied Machine Learning to Predict Healthcare Utilization Based on Socioeconomic Determinants of Care

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ABSTRACT

OBJECTIVES: To determine if it is possible to risk-stratify avoidable utilization without clinical data and with limited patient-level data.

STUDY DESIGN: The aim of this study was to demonstrate the influences of socioeconomic determinants of health (SDH) with regard to avoidable patient-level healthcare utilization. The study investigated the ability of machine learning models to predict risk using only publicly available and purchasable SDH data. A total of 138,115 patients were analyzed from a deidentified database representing 3 health systems in the United States.

METHODS: A hold-out methodology was used to ensure that the model's performance could be tested on a completely independent set of subjects. A proprietary decision tree methodology was used to make the predictions. Only the socioeconomic features—age group, gender, and race—were used in the prediction of a patient's risk of admission.

RESULTS: The decision tree–based machine learning approach analyzed in this study was able to predict inpatient and emergency department utilization with a high degree of discrimination using only purchasable and publicly available data on SDH.

CONCLUSIONS: This study indicates that it is possible to risk-stratify patients' risk of utilization without interacting with the patient or collecting information beyond the patient's age, gender, race, and address. The implications of this application are wide and have the potential to positively affect health systems by facilitating targeted patient outreach with specific, individualized interventions to tackle detrimental SDH at not only the individual level but also the neighborhood level.

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As defined by the World Health Organization and recognized by HHS, social determinants of health (SDH) are the conditions in which people live, work, play, and age. SDH affect a wide range of health-related outcomes, such as chronic conditions, preventable hospitalizations, morbidity, and mortality.[1,2] Decades of study results have found that sociodemographic status, racial and ethnic disparities, and individual behaviors directly correlate with an increase in the prevalence and incidence of chronic diseases.[3-5] In the United States, chronic diseases have contributed significantly to the rise in healthcare costs, with approximately 90% of annual healthcare expenditures—$3.3 trillion—attributed to caring for patients with chronic and mental health conditions.[6] Almost half of all Americans suffer from at least 1 chronic disease (eg, cancer, heart disease, stroke, chronic obstructive pulmonary disease, diabetes),[7-9] and two-thirds of deaths are caused by 1 or more of these chronic diseases. In addition, nationwide trends show a projected overall increase in chronic conditions.[10,11] Thus, it is imperative to address SDH not only at the individual level but at the population level as well.

Associations between economic inequality and health disparities exist in the United States; for example, residents of impoverished communities are at a higher risk of mental health issues, chronic diseases, increased mortality, and lower life expectancy.[12] Inequalities include lack of access to healthy food, with 17.4 million households considered food insecure[13]; decreased receipt of preventive medical care, with 1 in 4 individuals without a primary care provider[14]; 3.6 million people failing to obtain medical care due to transportation barriers[10]; and 65.9% of food assistance program clients reporting the necessity to choose between food and medical care.[15] The need for providers and communities to address SDH is apparent; however, healthcare providers have limited ability and limited access to do so within their existing workflow. Entering SDH data in electronic health records (EHRs) is predominantly a manual documentation process completed by providers with a limited range of determinants and relies on patients' self-report accuracy.[16,17] From a healthcare management approach, there is no evidence-based screening recommendation for SDH; however, several policy statements support screening patients for disparities.[18,19] According to a recent Kaiser Permanente survey of 1006 US adults 18 years or older demographically matched to represent the US population per Census data, 97% of respondents indicated that their healthcare provider should ask about social needs during medical visits and 80% expressed a desire for their healthcare provider to share information about resources to address their individual needs.[20]

TAKEAWAY POINTS

This investigation demonstrates that it is possible to predict individual hospital and emergency department utilization using publicly available data on socioeconomic determinants of care and purchased behavioral data, without requiring clinical risk factors.

- It is possible to risk-stratify patients' risk of utilization without interacting with the patient or collecting information beyond the patient's age, gender, race, and address.
- The implications of this application are wide and have the potential to positively affect health systems by facilitating targeted patient outreach with specific, individualized interventions to tackle detrimental social determinants of health at not only the individual level but also the neighborhood level.

Recent changes in healthcare policies and initiatives, including the introduction of the Accountable Health Communities established by the Patient Protection and Affordable Care Act (ACA),[16,21] are aimed toward reducing health inequalities. Such changes direct attention to the health-related social needs of Medicare and Medicaid beneficiaries and how addressing those needs can drive improvements in population health.[22] In addition, expansions made to CMS' Medicare Advantage program include a greater level of coverage for SDH. Coverage plans now include services like telemonitoring, benefits for over-the-counter medications, and rides to medical appointments for patients without transportation.[23,24] This expansion requires more data sources to track new kinds of information that are not readily available within the EHR.[25]

Current analyses, predictive models, and prevention initiatives focus on addressing SDH at the population level or the zip code level.[26-30] The shortcoming of this approach is a gap in addressing the individual patient's needs, such as defining clinical action steps that are relevant to the patient as opposed to an overall population approach. Advancements in cognitive science allow for the analysis of individual contributions of SDH at the patient level, informing appropriate interventions that can reduce the risk of negative health outcomes such as preventable readmissions and/or hospitalizations.[31] Additionally, increasing access to SDH based on geography (ie, Census Data Application Programming Interface) and the ability to purchase individual behavioral indexes may decrease the need to collect large sets of data from individual patients.

The aim of this study is to demonstrate the influences of socioeconomic determinants of health with regard to utilization at the individual level. Given what is known about the contribution of socioeconomic determinants of health, machine learning should be able to predict utilization independent of the patient's clinical condition while defining which determinants confer the greatest risk. The study will investigate the ability to predict risk with publicly available and purchasable SDH data.

METHODS

Patient Sample

We selected 138,115 patients from a deidentified database representing 3 health systems in the United States. The patient sample was selected to develop the most generalizable model. Both adult and pediatric patients were included, health systems were chosen from 3 diverse geographical areas, and all patients with at least 1 ambulatory, emergency department (ED), or inpatient visit during the month of November 2018 were included. The health systems were in urban Ohio, urban Georgia, and rural Alabama.

Data Source

The sole data source for this study was a deidentified database that included billing data and socioeconomic determinants of care. Billing data were collected directly from the health systems' EHRs. Socioeconomic elements had previously been collected from publicly available sources such as the US Census Bureau, US Department of Agriculture, and National Oceanic and Atmospheric Administration. The full Census data set, including poverty, income, household size, transportation, employment, and neighborhood characteristics, was considered by the model. A few data elements are unclear in the government references: neighborhood in-migration (the percentage of households that have moved to the neighborhood in the past 12 months), group living quarters (individuals living in college residence halls, residential treatment centers, skilled nursing facilities, group homes, military barracks, correctional facilities, and workers' dormitories), and purchasing channel preference (how individuals shop [eg, over the internet]).[32]

Behavioral data had been purchased from third-party data vendors such as Acxiom, Experian, and TransUnion. Individual behavioral data included elements such as history of internet searches on health conditions, purchasing channels, and life stage. All purchased data are indexes indicating preferences, and no transactional-level data were used. The purpose of the behavioral data is to enhance the model with individual preferences and behaviors. Publicly available data had been collected at the Census tract level, and behavioral data had been collected at the individual level. Race was defined by the race information provided by the health systems in their billing data.

Outcome Measures

The principal outcome measures of this study were any inpatient/ED utilization in 90 days (December 1, 2018, to February 28, 2019). Secondary outcomes included inpatient admission within 90 days,

TABLE 1. Population of Training and Testing (hold-out) Sets (N = 138,115)

	Training Set, n (%)	Testing (hold-out) Set, n (%)
Patients	97,039 (70.3)	41,076 (29.7)
Gender		
Female	59,929 (59.7)	24,438 (59.6)
Male	39,110 (40.3)	16,588 (40.4)
Race		
White or Caucasian	59,512 (61.3)	24,987 (60.8)
Black or African American	17,313 (17.9)	7102 (17.3)
Hispanic	1038 (1.1)	472 (1.2)
Asian or Pacific Islander	504 (0.5)	203 (0.5)
Unknown or other	18,612 (19.2)	8312 (20.2)
Age group in years		
0-<1	5118 (5.3)	2034 (5.0)
1-<18	9075 (9.4)	3908 (9.5)
18-30	9944 (10.3)	4182 (10.2)
31-50	15,500 (16.0)	6570 (16.0)
51-55	5262 (5.4)	2261 (5.5)
56-60	6544 (6.7)	2720 (6.6)
61-65	7322 (7.6)	2954 (7.2)
66-75	17,045 (17.6)	7364 (17.9)
≥76	21,215 (21.9)	9074 (22.2)
Unknown	14 (0.0)	9 (0.0)
Visits		
Inpatient admission or ED visit	4840 (5.0)	1933 (4.7)
Inpatient admission	2218 (2.3)	814 (2.0)
Avoidable admission	1572 (1.6)	594 (1.4)
ED visit	3102 (3.2)	1326 (3.2)

ED indicates emergency department.

Agency for Healthcare Research and Quality–defined avoidable inpatient admission within 90 days, and ED visit within 90 days.

Data Standards

Standard claim ontologies were used for billing data. Publicly available data and purchased data were used in their native form without transformation.

Machine Learning Approach

We split the patient population into 2 randomly selected groups: 70.3% of the patient population (training data) and 29.7% of the patient population (testing data). A hold-out methodology was used, meaning there was no overlap between patients in the training and testing sets; a random selection of patients was "held out" (ie, not included) in the training of the model. Therefore, the performance of the model could be tested on a completely independent set of subjects. A proprietary decision tree methodology was used to make the predictions. Decision trees are a group of supervised machine learning approaches that predict outcomes by generating potentially complex classification algorithms. Only the socioeconomic features—age group, gender, and race—were used in the prediction of a patient's risk of admission. No location data (ie, zip code, state, country) were considered by the model in order to limit any impact that regional differences in propensity of utilization might have on the predictions. Claims data were also used to identify the primary and secondary study outcomes.

Analysis

The performance of the machine learning algorithm to predict which patients would have a primary outcome was determined for both the training and testing sets. The area under the curve (AUC) for the receiver operating characteristic was calculated for both the training and testing sets for the primary outcome of inpatient or ED utilization within 90 days, as well as for the secondary outcomes of inpatient admission, avoidable admission, and ED visit. The sensitivity, specificity, positive predictive value, and negative predictive value were calculated in the testing set for the primary and secondary outcomes using a threshold of the top 30% highest-risk patients as the at-risk population. The highest-weighted socioeconomic values at the individual level were determined and aggregated across the population to determine the features most associated with determining risk.

RESULTS

The patients included in this study reflect a general population of patients (**Table 1**), both pediatric and adult. The population was 59.7% female and 61.1% Caucasian, and 85.4% of the patients were adults (≥18 years). The primary outcome occurred in 4.9% of the population.

The machine learning approach was able to predict utilization with a high degree of discrimination (**Table 2**). The event rates for inpatient hospitalization or ED visit, ED visit, inpatient hospitalization, and avoidable inpatient hospitalization were 4.7%, 3.2%, 2.0%, and 1.5%, respectively. The AUC for the primary outcome was 0.84 in the training set and 0.83 in the testing set. The testing AUCs ranged from 0.78 to 0.84 for the secondary outcomes. Sensitivity was 0.73 or greater for all outcomes, and specificity was 0.71 or greater, when 30% of the population was determined to be at risk of an event. The sensitivity values of the predictions for inpatient hospitalization or ED visit, ED visit, inpatient hospitalization, and avoidable inpatient hospitalization were 0.79, 0.82, 0.73, and 0.75, respectively.

Nineteen categories of SDH contributed to the branching of the decision tree algorithm. The relative values of the SDH are shown in **Table 3**. The SDH most associated with risk was air quality, which had a relative value more twice that of the next determinant, income. Air quality had a relative value more than 30-fold higher than the lowest-weighted determinant, percentage in group living quarters, which represents the number of people who are not living in housing units and instead are living in group quarters (eg, nursing homes, missions, shelters). Both air quality and income were more

TABLE 2. Model Performance for Predicting Inpatient Admissions, ED Visits, and Avoidable Inpatient Admissions

	AUC		Testing (hold-out) Performance: Top 30% of Patients at Risk				
	Training Set	Testing (hold-out) Set	Incidence (%)	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value
Inpatient admission or ED visit within 90 days	0.84	0.83	4.7	0.79	0.72	0.12	0.99
ED visit within 90 days	0.85	0.84	3.2	0.82	0.72	0.09	0.99
Any inpatient visit within 90 days	0.80	0.79	2.0	0.73	0.71	0.05	0.99
Avoidable inpatient visit within 90 days	0.80	0.78	1.5	0.75	0.71	0.04	0.99

AUC indicates area under the curve; ED, emergency department.

important to the decision-making capability of the model than age, ethnicity, or gender. Neighborhood in-migration, transportation, and purchasing channel preferences were more important than ethnicity or gender. Only 3 socioeconomic features influenced the model's decision-making capability less than gender: retail access, employment sector, and percentage in group living quarters.

DISCUSSION

This study demonstrates that it is possible to generate a highly accurate model to predict inpatient and ED utilization using decision tree–based machine learning with purchasable and publicly available data on SDH. All the data used in the analysis are available without collecting information directly from patients. Therefore, this study indicates that it is possible to risk-stratify patients' risk of utilization without interacting with the patient or collecting information beyond the patient's age, gender, race, and address. The implications of this application are wide and have the potential to positively affect health systems by facilitating targeted patient outreach with specific, individualized interventions to tackle detrimental SDH at not only the individual level but also the neighborhood level.

Multiple recent studies have found positive correlations between poor air quality and increased utilization.[33,34] A RAND study of California in 2012 found that, from 2005 to 2007, failure to meet federal clean air standards resulted in 29,808 hospitalizations and ED visits, with more than $190 million in costs from inpatient visits.[35] It was expected that air quality would be an important feature in determining risk, but the finding that it was the top contributing feature was unexpected. Air quality in this study includes factors that consider both fine particles and ozone.

Low income and poverty are associated with poor health outcomes and high healthcare utilization.[36] In 2017, 39.7 million Americans lived in poverty in the United States.[37] Individuals living in impoverished neighborhoods have been found to have lower health status and increased risk of mental health problems compared with those in wealthy and well-educated neighborhoods.[38,39] Impoverished neighborhoods commonly have limited resources, inadequate schools, crime, and violence. Individual poverty is associated with

TABLE 3. Relative Values of Socioeconomic Determinants of Health and Demographics

Category	Relative Value
Socioeconomic determinant of health	
Air quality	1.000
Income	0.370
Neighborhood in-migration	0.079
Transportation	0.070
Purchasing channel preferences	0.062
Health literacy	0.053
Population density	0.047
Social support	0.043
Education	0.040
Financial security	0.036
Housing stability	0.036
Food access	0.035
Employment opportunities	0.024
Environmental health hazard exposure	0.015
Digital fluency	0.015
Neighbor language (primary): English (%)	0.013
Retail access	0.008
Employment sector	0.005
Percentage in group living quarters	0.003
Demographic	
Age	0.182
Race/ethnicity	0.059
Gender	0.010

negative physiological responses from increased stress, including increased blood pressure and cortisol levels.[40] As expected, income level is a highly ranked factor for predicting utilization.

In contrast, neighborhood in-migration and purchasing channel preferences were, to our knowledge, not previously identified as predictors of hospital or ED utilization. Given the decision tree nature of the machine learning algorithm, it is possible that neighborhood in-migration has a dual effect. When it represents rapid growth, it may reduce the risk of healthcare utilization. However, when it represents lack of housing stability, it may increase an individual's risk.

Inadequate transportation poses many barriers to accessible healthcare, preventive screenings, and the management of chronic conditions.[41] Approximately 3 million children miss a healthcare appointment each year because of inaccessible transportation.[42] These challenges are found in both rural and urban communities, with both exhibiting lack of vehicle access, long travel distances, and extensive travel times.[43] Overall, lack of reliable transportation has been found to be associated with poor health outcomes.

Purchasing channels reflect digital knowledge, digital access, or simply behavioral preferences that translate to how individuals interact with healthcare systems and providers. Various research studies have identified that lack of digital access limits the ability to use technology for health-related purposes and prevents patients from using mobile technologies that support healthy behaviors. Internet access and usage hold a direct association with health literacy, which is the ability to comprehend basic healthcare information and use it to make informed healthcare decisions.[44,45] Further investigation is needed to determine how these characteristics contribute to an individual patient's risk.

The final 14 SDH categories, ranked by descending relative value, were health literacy, population density, social support, education, financial security, housing stability, food access, employment opportunities, environmental health hazard exposure, digital fluency, neighbor language (primary): English, retail access, employment sector, and percentage in group living quarters. Interactive relationships exist among SDH, such as living in a high population density area, having low education levels, and higher rates of poverty.[46] That said, the decision tree–based machine learning approach was able to identify the relative values of these SDH categories.

Addressing the root cause of inequalities in the community runs in parallel with solving nationwide health issues such as food insecurity and limited access to care.[47] Through the ACA, nonprofit hospitals are required to conduct community health needs assessments and construct community interventions every 3 years.[48,49] The ACA-enacted tax exemption requirement aids in encouraging accountability in these hospitals.[18] However, many hospitals and affiliated organizations may lack the resources and competencies to strategically address community health initiatives that commonly fall outside of basic clinical care. Other technologies including EHRs are making advances to collect patient-reported socioeconomic determinants of care. However, these technologies have shown little advancement in the ability to understand the effects of socioeconomic determinants of care at the individual and community levels.[9] We envision these health systems to be able to strategically target those initiatives with the technology and methods included within this study. Integration would consist of a simplistic geospatial visualization and be applied across multiple clinical disciplines. Primary care workflows would focus on the effort in reducing socioeconomic disparities such as access to food, exposure to environmental hazards, and access to transportation. A primary care physician may use this as a tool to identify areas on which to focus socioeconomic screening and topics to problem-solve regarding overcoming barriers with patients. A community care coordinator would find this technology useful for outreach programs (eg, patient follow-up with prescribed diet). With healthcare organizations spending millions of dollars on treating those in the community and with federal policy focusing on community impact, this type of solution ensures maximum effectiveness for driving positive health-related outcomes.

Finally, this approach to integrating SDH to assess risk of healthcare utilization addresses limitations in many previous studies. For example, this model has been developed using almost 140,000 patients in both rural and urban settings in multiple US regions, which increases the confidence in generalizability. Given that there is no additional documentation required by clinicians, SDH can be considered for holistic patient care without disruption to existing clinical workflows and is not limited by variations in provider documentation.[27,29] Additionally, with no required assessment and documentation of individual SDH, many more risk factors can be integrated into the model for consideration, which can more accurately identify the appropriate interventions at the patient level.[26]

Limitations

The patient population is based on a single month of active encounters and includes patients from just 3 geographic areas. The patient population may not be fully generalizable to the US population because of the diversity across populations and each community's unique socioeconomic environment. Also, the decision tree methodology determines only associates that are predictive and does not mean that the identified factors are causative. The lack of causation may limit the actionability of this research.

CONCLUSIONS

This investigation demonstrates that it is possible to predict hospital and ED utilization without data on clinical risk factors. Instead, predictive features are based on publicly available socioeconomic determinants of care and purchasable behavioral data. This study highlights the significant influence of SDH on individuals' health and healthcare use. It is an important advancement in tackling disparities in healthcare because risk can be assessed without gathering information directly from the patient and thus can be incorporated efficiently into workflows. ■

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REFERENCES

1. Closing the gap in a generation: health equity through action on the social determinants of health. World Health Organization website. who.int/social_determinants/thecommission/finalreport/en. Published 2008. Accessed July 1, 2019.
2. Social determinants of health. HealthyPeople.gov website. healthypeople.gov/2020/topics-objectives/topic/social-determinants-of-health. Accessed July 1, 2019.
3. Hale N, Probst J, Robertson A. Rural area deprivation and hospitalizations among children for ambulatory care sensitive conditions. *J Community Health*. 2016;41(3):451-460. doi: 10.1007/s10900-015-0113-2.
4. Adler NE, Ostrove JM. Socioeconomic status and health: what we know and what we don't. *Ann N Y Acad Sci.* 1999;896:3-15. doi: 10.1111/j.1749-6632.1999.tb08101.x.
5. DeSalvo KB, Wang YC, Harris A, Auerbach J, Koo D, O'Carroll P. Public health 3.0: a call to action for public health to meet the challenges of the 21st century. *Prev Chronic Dis.* 2017;14:E78. doi: 10.5888/pcd14.170017.
6. Health and economic costs of chronic diseases. CDC website. cdc.gov/chronicdisease/about/costs/index.htm. Updated October 23, 2019. Accessed October 25, 2019.
7. Chronic conditions among older Americans. AARP website. assets.aarp.org/rgcenter/health/beyond_50_hcr_conditions.pdf. Accessed July 2, 2019.
8. Kumbhare SD, Beiko T, Wilcox SR, Strange C. Characteristics of COPD patients using United States emergency care or hospitalization. *Chronic Obstr Pulm Dis*. 2016;3(2):539-548. doi: 10.15326/jcopdf.3.2.2015.0155.
9. Arredondo A, Recaman AL, Azar A. Socioeconomic determinants and health disparities in relation to hypertension in middle-income countries. *Am J Hypertens.* 2017;30(4):355-357. doi: 10.1093/ajh/hpx016.
10. Syed ST, Gerber BS, Sharp LK. Traveling towards disease: transportation barriers to healthcare access. *J Community Health.* 2013;38(5):976-993. doi: 10.1007/s10900-013-9681-1.
11. 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. doi: 10.1016/j.amepre.2015.02.018.
12. Poverty. HealthyPeople.gov website. healthypeople.gov/2020/topics-objectives/topic/social-determinants-health/interventions-resources/poverty. Accessed July 15, 2019.
13. Food insecurity. HealthyPeople.gov website. healthypeople.gov/2020/topics-objectives/topic/social-determinants-health/interventions-resources/food-insecurity. Accessed July 2, 2019.
14. Access to health services. HealthyPeople.gov. healthypeople.gov/2020/leading-health-indicators/2020-lhi-topics/Access-to-Health-Services. Accessed July 10, 2019.
15. Weinfield NS, Mills G, Borger C, et al. Hunger in America 2014: national report. Feeding America website. help.feedingamerica.org/HungerInAmerica/hunger-in-america-2014-full-report.pdf. Published August 2014. Accessed July 2, 2019.
16. 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. doi: 10.1370/afm.1903.
17. Adler NE, Stead WW. Patients in context—EHR capture of social and behavioral determinants of health. *N Engl J Med.* 2015;372(8):698-701. doi: 10.1056/NEJMp1413945.
18. Young GJ, Chou CH, Alexander J, Lee SY, Raver E. Provision of community benefits by tax-exempt U.S. hospitals. *N Engl J Med*. 2013;368(16):1519-1527. doi: 10.1056/nejmsa1210239.
19. Guise NB, Koonce TY, Kusnoor SV, et al. Institute of Medicine measures of social and behavioral determinants of health: a feasibility study. *Am J Prev Med.* 2017;52(2):199-206. doi: 10.1016/j.amepre.2016.07.033.
20. Kaiser Permanente Research: social needs in America. Kaiser Permanente website. about.kaiserpermanente.org/content/dam/internet/kp/comms/import/uploads/2019/06/KP-Social-Needs-Survey-Key-Findings.pdf. Published June 4, 2019. Accessed July 10, 2019.
21. Hoffman GJ, Hsuan C, Braun T, Ponce N. Health equity and hospital readmissions: does inclusion of patient functional and social complexity improve predictiveness? *J Gen Intern Med*. 2019;34(1):26-28. doi: 10.1007/s11606-018-4635-z.
22. Artiga S, Hinton E. Beyond health care: the role of social determinants in promoting health and health equity. Kaiser Family Foundation website. files.kff.org/attachment/issue-brief-beyond-health-care. Published May 2018. Accessed July 10, 2019.
23. Sorbero ME, Kranz AM, Bouskill KE, Ross R, Palimaru AI, Meyer A. Addressing social determinants of health needs of dually enrolled beneficiaries in Medicare Advantage plans. RAND Corporation website. rand.org/pubs/research_reports/RR2634.html. Published 2018. Accessed July 10, 2019.
24. New options in Medicare Advantage: addressing the social determinants of health and more. American Hospital Association website. aha.org/system/files/2019-01/new-options-medicare-advantage-addressing-social-determinants-of-health.pdf. Published January 2019. Accessed July 10, 2019.
25. CMS expands Medicare Advantage coverage for social determinants of health. PricewaterhouseCoopers website. pwc.com/us/en/industries/health-industries/health-research-institute/medicare-advantage-coverage-for-social-determinants.html. Accessed July 10, 2019.
26. 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. doi: 10.1093/jamia/ocx130.
27. Vest JR, Grannis SJ, Haut DP, Halverson PK, Menachemi N. Using structured and unstructured data to identify patients' need for services that address the social determinants of health. *Int J Med Inform*. 2017;107:101-106. doi: 10.1016/j.ijmedinf.2017.09.008.
28. Kepper MM, Southern MS, Theall KP, et al. A reliable, feasible method to observe neighborhoods at high spatial resolution. *Am J Prev Med*. 2017;52(1S1):S20-S30. doi: 10.1016/j.amepre.2016.06.010.
29. Hewner S, Casucci S, Sullivan S, et al. Integrating social determinants of health into primary care clinical and informational workflow during care transitions. *EGEMS (Wash DC)*. 2017;5(2):2. doi: 10.13063/2327-9214.1282.
30. Cottrell EK, Gold R, Likumahuwa S, et al. Using health information technology to bring social determinants of health into primary care: a conceptual framework to guide research. *J Health Care Poor Underserved*. 2018;29(3):949-963. doi: 10.1353/hpu.2018.0071.
31. Parikh RB, Jain SH, Navathe AS. The sociobehavioral phenotype: applying a precision medicine framework to social determinants of health. *Am J Manag Care*. 2019;25(9):421-423.
32. The group quarters population and the American Community Survey. In: National Research Council. *Small Populations, Large Effects: Improving the Measurement of the Group Quarters Population in the American Community Survey*. Washington, DC: The National Academies Press; 2012:19-32.
33. Pan HH, Chen CT, Sun HL, et al. Comparison of the effects of air pollution on outpatient and inpatient visits for asthma: a population-based study in Taiwan. *PLoS One.* 2014;9(5):e96190. doi: 10.1371/journal.pone.0096190.
34. Yoo EH, Brown P, Eum Y. Ambient air quality and spatio-temporal patterns of cardiovascular emergency department visits. *Int J Health Geogr*. 2018;17(1):18. doi: 10.1186/s12942-018-0138-8.
35. Romley JA, Hackbarth A, Goldman DP. The impact of air quality on hospital spending. *RAND Health Q*. 2012;2(3):6.
36. Hadler JL, Yousey-Hindes K, Pérez A, et al. Influenza-related hospitalizations and poverty levels—United States, 2010-2012. *MMWR Morb Mortal Wkly Rep*. 2016;65(5):101-105. doi: 10.15585/mmwr.mm6505a1.
37. Income and poverty in the United States: 2017. United States Census Bureau website. census.gov/library/publications/2018/demo/p60-263.html. Published September 12, 2018. Accessed July 10, 2019.
38. Braveman PA, Cubbin C, Egerter S, Williams DR, Pamuk E. Socioeconomic disparities in health in the United States: what the patterns tell us. *Am J Public Health*. 2010;100(suppl 1):S186-S196. doi: 10.2105/ajph.2009.166082.
39. Stevens CD, Schriger DL, Raffetto B, Davis AC, Zingmond D, Roby DH. Geographic clustering of diabetic lower-extremity amputations in low-income regions of California. *Health Aff (Millwood)*. 2014;33(8):1383-1390. doi: 10.1377/hlthaff.2014.0148.
40. Hodgkinson S, Godoy L, Beers LS, Lewin A. Improving mental health access for low-income children and families in the primary care setting. *Pediatrics*. 2017;139(1):e20151175. doi: 10.1542/peds.2015-1175.
41. Syed ST, Gerber BS, Sharp LK. Traveling towards disease: transportation barriers to health care access. *J Community Health*. 2013;38(5):976-993. doi: 10.1007/s10900-013-9681-1.
42. Grant R, Gracy D, Goldsmith G, Sobelson M, Johnson D. Transportation barriers to child health care access remain after health reform. *JAMA Pediatr*. 2014;168(4):385-386. doi: 10.1001/jamapediatrics.2013.4653.
43. Social determinants of health series: transportation and the role of hospitals. American Hospital Association website. aha.org/ahahret-guides/2017-11-15-social-determinants-health-series-transportation-and-role-hospitals. Accessed July 10, 2019.
44. Gordon NP, Hornbrook MC. Differences in access to and preferences for using patient portals and other eHealth technologies based on race, ethnicity, and age: a database and survey study of seniors in a large health plan. *J Med Internet Res*. 2016;18(3):e50. doi: 10.2196/jmir.5105.
45. Fridsma DB. Re: request for comment—actions to accelerate adoption and accessibility of broadband-enabled health care solutions and advanced technologies. American Medical Informatics Association website. amia.org/sites/default/files/AMIA-Response-to-FCC-Notice-on-Accelerating-Broadband-Health-Tech-Availability.pdf. Published May 24, 2017. Accessed July 15, 2019.
46. Song R, Hall HI, Harrison KM, Sharpe TT, Lin LS, Dean HD. Identifying the impact of social determinants of health on disease rates using correlation analysis of area-based summary information. *Public Health Rep*. 2011;126(suppl 3):70-80. doi: 10.1177/00333549111260S312.
47. Sullivan HR. Hospitals' obligations to address social determinants of health. *AMA J Ethics*. 2019;21(3):E248-E258. doi: 10.1001/amajethics.2019.248.
48. Requirements for 501(c)(3) hospitals under the Affordable Care Act – section 501(r). Internal Revenue Service website. irs.gov/charities-non-profits/charitable-organizations/requirements-for-501c3-hospitals-under-the-affordable-care-act-section-501r. Updated September 20, 2019. Accessed September 22, 2019.
49. Frieden TR. A framework for public health action: the health impact pyramid. *Am J Public Health*. 2010;100(4):590-595. doi: 10.2105/ajph.2009.185652.

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