Received: 22 October 2023 | Revised: 8 May 2024 | Accepted: 26 June 2024

DOI: 10.1002/emp2.13240

CLINICAL CONCEPTS

Pediatrics

A novel tool using social and environmental determinants of health to assess pediatric asthma in the emergency department

Danica B. Liberman MD, MPH[1,2,3] | Jonathan S. Tam MD[2,4] | Anna M. Cushing MD[1,2] | Juan Espinoza MD[2,5]

[1]Division of Emergency and Transport Medicine, Children's Hospital Los Angeles, Los Angeles, California, USA

[2]Department of Pediatrics, Keck School of Medicine, University of Southern California, Los Angeles, California, USA

[3]Department of Population and Public Health Sciences, Keck School of Medicine, University of Southern, Los Angeles, California, USA

[4]Division of Clinical Immunology and Allergy, Children's Hospital Los Angeles, Los Angeles, California, USA

[5]Division of General Pediatrics, Children's Hospital Los Angeles, Los Angeles, California, USA

Correspondence
Danica B. Liberman, Division of Emergency and Transport Medicine, Children's Hospital Los Angeles, 4650 Sunset Blvd. Mailstop #113, Los Angeles, CA 90027, USA.
Email: dliberman@chla.usc.edu

Funding information
U.S. National Institutes of Health; National Center for Advancing Translational Sciences, Grant/Award Numbers: UL1TR000130, UL1TR001855

Abstract

Asthma, the most common chronic disease in children, affects more than 4 million children in the United States, disproportionately affecting those who are economically disadvantaged and racial and ethnic minorities. Studies have shown that the racial and ethnic disparities in asthma outcomes can be largely explained by environmental, socioeconomic and other social determinants of health (SDoH). Utilizing new approaches to stratify disease severity and risk, which focus on the underlying SDoH that lead to asthma disparity, provides an opportunity to disentangle race and ethnicity from its confounding social determinants. In particular, with the growing use of geospatial information systems, geocoded data can enable researchers and clinicians to quantify social and environmental impacts of structural racism. When these data are systematically collected and tabulated, researchers, and ultimately clinicians at the bedside, can evaluate patients' neighborhood context and create targeted interventions toward those factors most associated with asthma morbidity. To do this, we have designed a view (mPage in the Cerner electronic health record) that centralizes key clinical information and displays it alongside SDoH variables shown to be linked to asthma incidence and severity. Once refined and validated, which is the next step in our project, our goal is for emergency medicine clinicians to use these data in real time while caring for patients with asthma. Our multidisciplinary, patient-centered approach that leverages modern informatics tools will create opportunities to better triage patients with asthma exacerbations, choose the best interventions, and target underlying determinants of disease.

KEYWORDS
asthma, disparities, emergency medicine, geospatial information systems, social determinants of health

1 | INTRODUCTION

Asthma, the most common chronic disease in children, affects more than 4 million children in the United States.[1] Asthma disproportionately affects economically disadvantaged groups and is more prevalent among racial and ethnic minorities, including non-Hispanic Black (11.6%) and American Indian and Alaskan Native (9.2%) children, compared with non-Hispanic White children (5.5%).[1,2] Moreover, Black children are more likely to visit the emergency department (ED), require hospitalization, and die from asthma than White children.[1,3,4]

Studies have shown that the racial and ethnic disparities in asthma outcomes can be largely explained by environmental, socioeconomic, and other social determinants of health (SDoH), also referred to as social drivers of health.[5–15] As described by the World Health Organization Commission on the Social Determinants of Health, the term social determinants of health contains both the social factors that influence health and the structural processes that result in the unequal distribution of these factors among groups.[16] Prior studies highlight how asthma morbidity is directly linked to SDoH and how patients from under-resourced communities are uniquely vulnerable.[17] Race, as a social construct, does not capture biological information. Instead, it is a highly imperfect proxy for racism, and more specifically, the likelihood that an individual will experience the systemic and structural effects of racism in the United States.

Utilizing new approaches to stratify disease severity and risk, which focus on the underlying SDoH that lead to asthma disparity, provides an opportunity to get to the core factors influencing disease incidence and morbidity. In particular, with the growing use of geospatial information systems, geocoded data can enable researchers and clinicians to actually quantify some of the social and environmental impacts on health and disease through variables like the Gini coefficient, Social Vulnerability Index, food access, and median household income.[18,19] By accounting for these more proximal concepts, we can get a better understanding of which factors actually drive worse outcomes. When these data are systematically collected and tabulated, researchers, and ultimately clinicians at the bedside, can evaluate patients' neighborhood context and social structures and create targeted interventions toward those factors most associated with asthma morbidity.[20,21]

2 | DEVELOPMENT AND DESIGN

2.1 | Project goal

Starting in 2019, a team from Children's Hospital Los Angeles (CHLA) and the University of Southern California (USC), supported by the Southern California Clinical and Translational Science Institute (SC CTSI), has worked to improve identification of SDoH influences and impacts on asthma health at the point of care. We aim to apply the social ecological model framework to describe and evaluate the dynamic relationship between individual factors and social and environmental factors in pediatric asthma.[22] By investigating the multiple layers of potential influences—societal, community, and interpersonal—we can identify key factors that critically impact an individual's health and contribute to asthma prevalence and morbidity.

2.2 | Project team and setting

Our multidisciplinary team includes faculty from general pediatrics, pediatric emergency medicine, and pediatric allergy/immunology, resident and fellow trainees, social workers, spatial scientists, and clinical informaticists. The attending physicians working on this project hold faculty appointments at USC, making cross-campus and interdisciplinary collaboration on research projects such as this one more feasible. CHLA, where the faculty, trainees, and social workers involved in this project work clinically, is a safety net free-standing tertiary care 391-bed children's hospital located in urban Los Angeles. The emergency department at CHLA had 97,176 visits in 2023, with 4,215 patients presenting with asthma exacerbations. While most patients seeking care in the ED at CHLA are from within the Los Angeles city limits, the hospital maintains a large catchment area, with some patients traveling from more rural regions within and outside Los Angeles County for pediatric-specific emergency care.

2.3 | Project development

Figure 1 shows a process map for our Asthma SDoH Project. Once the project was approved and funded by SC CTSI, the project lead (J.E.) assembled a group of key stakeholders who actively participated in and advised on the project. The stakeholders established a project charter and overall project plan. Three parallel work streams were established: (1) variable selection, (2) electronic health record (EHR) integration, and (3) risk score development. Stakeholders were invited to participate in any of the workstreams where their expertise was most valuable. A core project team that included authors J.E., D.L., A.C., and J.T., along with a project manager, participated in all three workstreams.

2.3.1 | Variable selection

To select the clinical variables, the team performed a literature review that included current asthma clinical guidelines and developed a list of relevant clinical factors. This list was refined with input from clinical experts from various disciplines. The list was then reviewed with EHR analysts to determine the feasibility of surfacing these variables in the EHR from structured data fields. The final list of clinical and demographic variables included is shown in Table 1. For geocoded variables, collaborators from the USC Spatial Sciences Institute provided the project team an overview of available data sources, existing variables, and the relevant literature that supports their use in asthma. Variables for inclusion had to be freely available from a reputable source with published methodology and have a known or suspected link with pediatric asthma outcomes. Table 2 shows the final 21

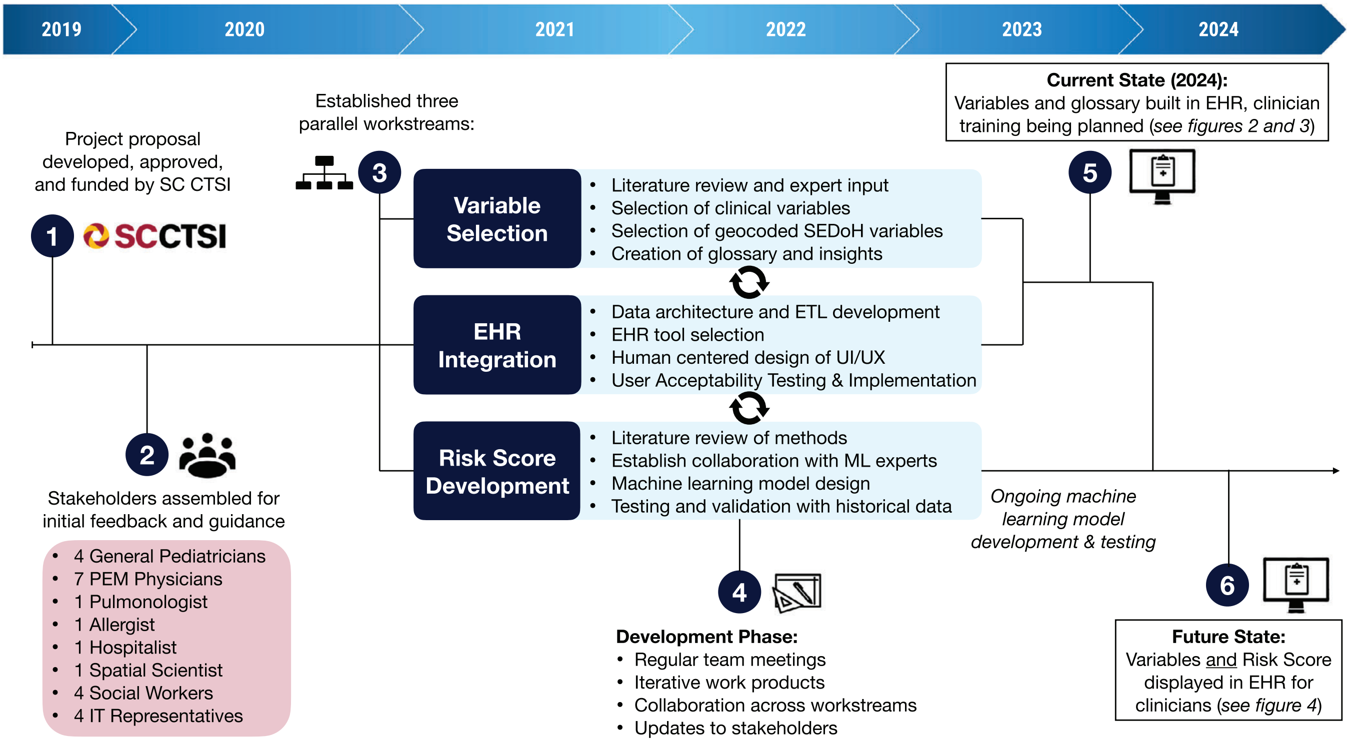

FIGURE 1 Process map for the development of the Asthma SDoH project. This process map graphically represents the overall project in six phases: (1) initial development, approval and funding by our CTSA, (2) organization of a representative stakeholder group to participate in and advise on the development of the project, (3) the creation of three separate work streams that moved different components of the projects forward in parallel, (4) an iterative development phase for all three workstreams, (5) the deployment of version in the EHR production environment, and (6) ongoing work to refine a machine learning algorithm that will be used to create a risk score for patients seen in the ED for asthma exacerbations. SC CTSI, Southern California Clinical and Translational Institute; ED, emergency department; EHR, electronic health record; ETL, extract, transform, and load; ML, machine learning; SDoH, social determinants of health; UI/UX, user interface and user experience.

TABLE 1 Clinical and demographic variables presented in the Asthma mPage.

Variable name	Variable description
Demographics	Includes address, race/ethnicity, and preferred language
BMI	Includes the most recent BMI percentile and *z*-score
ED visits	Shows the date and chief complaint of all ED visits in the past 12 months
Inpatient visits	Shows the date and chief complaint of all hospitalizations in the past 12 months
Clinic visits	Shows the data, location, and reason for visit for all outpatient encounters in the past 12 months
ICU visits	Shows the date and reason for all ICU stays in the past 12 months
Diagnosis	Shows if a patient has an ICD-10 Code in their problems and diagnoses list relevant to asthma
Inpatient meds	Shows which relevant asthma meds a patient received in the hospital in the last 12 months
Outpatient meds	Shows which relevant asthma meds a patient was prescribed in the last 12 months
Allergies	Shows the results of testing for specific allergens relevant to asthma
Asthma symptoms	Shows the results of the Pediatric Asthma Symptoms (PAS) and Asthma Control Test (ACT) assessments. If they have not been performed at this visit, there is a link to launch the assessment.
Most recent ED asthma action plan	Displays a link to the most recent ED asthma action plan in the last 12 months. If it has not been performed at this visit, there is a link to launch the module.
Most recent inpatient asthma action plan	Displays a link to the most recent Inpatient asthma action plan in the last 12 months. If it has not been performed at this visit, there is a link to launch the module.

Abbreviation: BMI, body mass index; ED, emergency department.

TABLE 2 Social determinants of health variables and their sources for the electronic health record Asthma mPage.

Variable name	Variable description	Variable Source
Air Quality Indicator–Asthma ER Visits	Air quality indicator–age-adjusted rate of ER visits for asthma per 10,000 persons.	CES
Air Quality Indicator–Ozone (O3)	Air quality indicator–Ozone (O3). Ozone pollution causes numerous adverse health effects, including acute upper and lower respiratory symptoms, reduced lung function, and exacerbation of lung disease. CalEnviroScreen values modeled from summer month maximum-value means for 2012–2014. The values are in parts per million. O3 concentrations in these data range between 0.026 and 0.068 ppm.	CES
Air Quality Indicator–PM2.5	Air quality indicator–Fine particulate matter $\leq$2.5 µm. PM2.5 includes extremely small particles and liquid droplets that when inhaled can penetrate deep into the lungs causing serious health problems. CalEnviroScreen values modeled from averages of quarterly means for 2012–2014. The values are in micrograms per cubic meter. PM2.5 values in these data range between 2 and 20 µg per cubic meter.	CES
Census Tract is Urban Flag	Urban/rural designation based on decennial census. Used here for food access, assumption is that greater distances will be traveled to grocery stores in rural locations.	USDA
Drink Water Index	The drinking water contaminant indicator considers measured chemical and bacterial contaminant levels; presence of multiple contaminants; and any past water system water-quality violations. CalEnviroScreen data (2005–2013) were aggregated from census blocks to tracts, weighted by population, and the state percentile value for each contaminant and violation type was summed for the overall score. The index ranges from 0 upwards, with higher values indicating greater concentrations of multiple contaminants.	CES
Food–Fraction of Population with Low Access	USDA Food Access Research Atlas data (2015) measure access to healthy and affordable food based on distance thresholds. This indicator estimates the percentage of the census tract population that live beyond 1 mile from the nearest supermarket for urban areas, or 10 miles for rural areas.	USDA
Food–Low-Access Tract	Low food access tract at 1 mile for urban areas or 10 miles for rural areas. The USDA Food Access Research Atlas considers a census tract to have low food access if a significant number (500) or share ($\geq$33%) of individuals in the tract lives beyond a specific distance from a supermarket, supercenter, large grocery store, or other source of healthy and affordable food.	USDA
Gini Inequality Coefficient	Income inequality is the extent to which income is distributed unevenly among a population. The Gini Index is a summary measure where higher values indicate greater inequality; the coefficient ranges from 0 (perfect equality, everyone receives an equal share) to 1 (perfect inequality).	ACS
Housing–Median Year Built	Median year housing units built. Housing quality is affected by a home's age, maintenance, structure, and design. Poor air quality; lack of insulation; and potential exposure to lead, asbestos, mold, or carbon monoxide are examples of factors associated with negative health outcomes.	ACS
Median Household Income	Estimated median annual household income in US dollars. These data range between $7461 and $250,000.	ACS
Pct Below 100% of Fed Poverty Level	Percentage of the population with estimated annual income below the federal poverty level.	ACS
Pct Below 200% of Fed Poverty Level	Percentage of the population with estimated annual income below 200% of the federal poverty level.	ACS
Pct HH that receive SNAP	Percentage of households receiving food stamps/SNAP.	ACS
Pct HH with limited English	Percentage of households that speak English less than very well.	ACS
Pct HS Grad–Age 25 or Over	Educational attainment; estimated percentage of the population age 25 and over who are high school graduates.	ACS
Population Density	Population density measures the number of persons per geographical area by dividing the total population by the total land area. It varies considerably across urban and rural areas and also across neighborhoods within cities. It is measured in persons per square kilometer.	ACS
SB535 Disadvantaged Community flag	Census tract is/is not a SB 535 Disadvantaged Community. These pollution-burdened communities represent the 25 percent highest scoring census tracts in California based on a suite of CalEnviroScreen indicators, including the three pollutant metrics we include here. SB 535 communities were specifically targeted for investment of proceeds from the States cap-and-trade program, one of several strategies used to reduce greenhouse gases that cause climate change, and are aimed at improving public health, quality of life, and economic opportunities.	CES

(Continues)

TABLE 2 (Continued)

Variable name	Variable description	Variable Source
Social Vulnerability Index	Social vulnerability measures community resilience to respond to or recover from threats to public health. The CDC SVI uses Census data for 15 social factors, including poverty, lack of access to transportation, and crowded housing, grouped into four themes. The index ranges from 0 to 1, with higher values indicating more vulnerable populations.	SVI
Total Tract Households	Number of households in a census tract	ACS
Total Tract Housing Units	Number of housing units in a census tract	ACS
Total Tract Population	Population of a census tract	ACS

Note: ACS: American Community Survey, 5-year estimates, 2015-2019. US Census Bureau, 2020. CES: CalEnviroScreen 3.0. June 2018 update. Office of Environmental Health Hazard Assessment (OEHHA), on behalf of the California Environmental Protection Agency (CalEPA). SVI: Social Vulnerability Index, 2018. Centers for Disease Control and Prevention. Agency for Toxic Substances and Disease Registry. Based on US Census data. USDA: Food Access Research Atlas, 2015. US Department of Agriculture, Economic Research Service, 2017.

SDoH variables selected for inclusion. Most of the variables are from national databases,[23,24] and those unique to California generally have similar data collected elsewhere, which will allow for generalization of this tool after internal and external validation of the risk score. A glossary explaining the variables, range of values, and relevance was developed and included in the EHR. To display the geocoded variables in the patient's EHR, the patient's address on record was geocoded in real time to the census tract, and then matched against a static database of the 21 variables for all census tracts in Southern California.

2.3.2 | EHR integration

We selected the Cerner mPage framework, which allows for custom displays of information combining Cerner Command Language scripts, HyperText Markup Language code, and application programming interfaces, as our development environment. Wireframe mockups of the mPage were developed and workshopped with clinicians to define the overall design. Once determined, EHR analysts created the mPage, validated the data, and then did a second round of testing with users to refine the design. After finalizing the design, mPages were published to an EHR staging environment so that realistic user acceptability testing could be conducted. The final versions of the mPages (Figure 2 and Figure S1) have been published to our production environment, but have not yet been made widely available to clinicians pending user training.

2.3.3 | Risk score development

Research to develop the risk stratification model using clinical and geocoded data is currently underway. We established a partnership with a team of machine learning researchers at the University of Tennessee to design a risk score algorithm based on their prior work to better identify patients at higher risk of asthma morbidity and increased healthcare utilization.[25] We are currently using retrospective data from CHLA to validate the existing algorithm from the University of Tennessee, which will then be followed by a period of prospective validation, and eventual incorporation into the EHR as a clinical decision support tool. Figure 3 shows a mockup of how this might be represented in the EHR.

2.4 | Current and future state

The clinical and social variables, along with the glossary, are in production mode in our EHR today and not yet available for clinician use in the ED. We anticipate training and education for emergency medicine clinicians and social workers in the near future. Following the training, we will gather feedback from emergency medicine clinicians and social workers at regular intervals, and improve the design based on their feedback. Once the risk score algorithm is added to the EHR, it will require critical ongoing evaluation for bias, predictive accuracy, and potential implications for change in clinical practice. As we perform additional evaluations, we plan to revisit the variables included (potentially narrowing or expanding them to improve their utility), the interface design, and risk score algorithm, with the ultimate goal of creating a tool that facilitates and enhances evidence-based patient care and disposition planning.

3 | IMPLICATIONS

Our project goal is for emergency medicine clinicians to use these data in real time while caring for patients with asthma. For instance, when evaluating a patient presenting with an asthma exacerbation, an emergency medicine clinician may begin the patient's encounter with the typical questions: events leading up to this exacerbation, historical triggers, controller medications, and past hospitalizations. However, following the history and examination, the clinician can open the asthma mPage (Figure S1) linked to that particular patient's EHR, which we have described above that houses additional relevant data. Here, the clinician can review this comprehensive page for key clinical information including previous asthma visits, past ICU admissions, asthma medications, and number of oral steroid courses, as well as social and

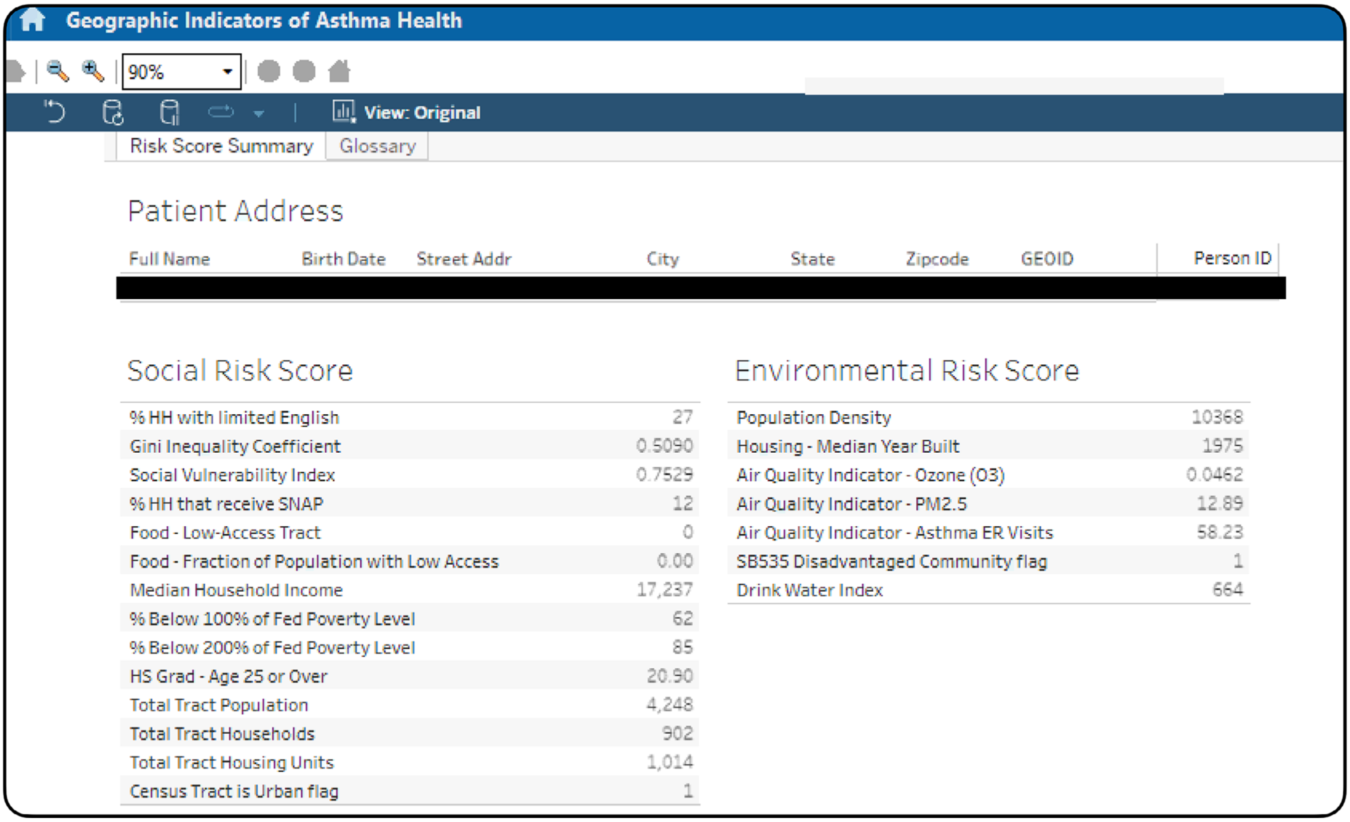

FIGURE 2 Screenshot of the current state Asthma mPage–social and environmental determinants of health (SDoH) data. This mPage has the *Risk Score Summary*, which shows the patient address (so the clinician can verify that it is correct) and the geocoded variables that comprise the social and environmental risk scores. These are the data currently available in the electronic health record (EHR), though not yet widely accessible by clinicians. It is likely that variables will change over time as we reassess their utility and currency.

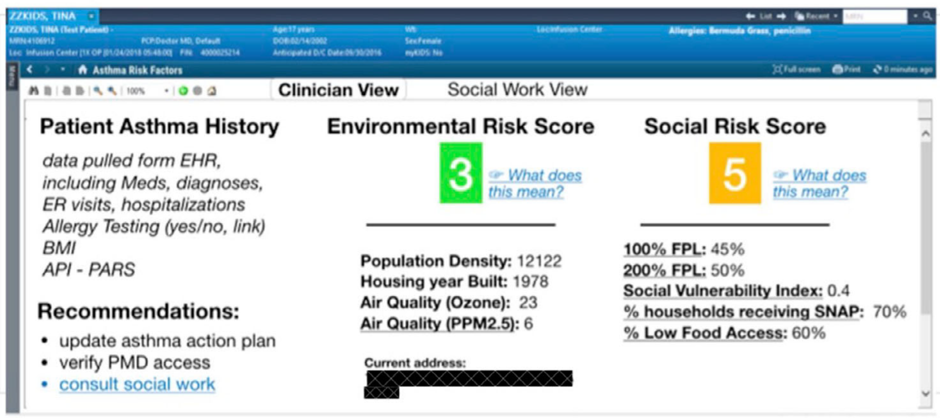

FIGURE 3 Mockup screenshot of the future state of the Asthma mPage. In the next iteration of the Asthma mPage, the goal is to display, in a single view, the clinical and social and environmental determinants of health (SDoH) data, along with composite risk scores for social and environmental factors. Research to develop the risk stratification model using clinical and geocoded data is currently underway.

environmental characteristics of their neighborhood, including poverty level and environmental exposure to pollutants.

To distill the large amount of raw data presented in the asthma mPage and help them assess disease severity and tailor management, clinicians will also be able to refer to the health risk scores (Figures 2 and 3) for a description and tabulation of the patient's clinical, social, and environmental determinants of health risk. Figure 2 details the different SDoH indicators, while Figure 3 crystallizes these variables into single risk scores for environmental and social risk. We anticipate that clinicians will utilize the consolidated risk scores in Figure 3 routinely, while the more elaborate breakdown of scoring in Figure 2 can be available to reference for those who are interested in more detail.

Our expectation is that presenting social and clinical data will help provide much needed context for clinicians, and lead to exploration of nonmedical factors that may potentially be addressed, including interventions already known to be effective at reducing asthma morbidity.[26] For instance, for patients with significant allergic triggers, clinicians may not only initiate antihistamine medications, but also provide housing resources for those describing substandard housing. Sophisticated and novel programs that provide in-home consultations, one-on-one asthma education, and even apartment remediation services, often in collaboration with health care systems, are gaining evidence-based traction.[27]

We believe that by combining clinical information with detailed contextual socioeconomic and environmental exposure data, we can create a more nuanced evaluation and risk stratification tool that considers the true underlying causes of disparities in asthma. Ultimately, we hope to show value in this tool by measuring outcomes, ranging from process metrics like frequency of use of the mPage and referrals placed to relevant community resources, to outcome metrics including improved Asthma Control Test scores and reductions in ED visits. Once refined internally, we plan to share this tool more broadly, with risk scores calculated for patients throughout the country using data pulled in from their local EHR and available databases for the SDoH variables.

Shifting focus to the true underlying factors driving disease incidence in asthma is vital but requires us to reconsider what we have been taught in the past about this disease. At the same time, we must take care to use this additional information about our patients and their social situations and resources thoughtfully and constructively. We hope it will further conversations with our patients and their families and facilitate a better understanding of our patients, while taking care to avoid the potential to perpetuate or exacerbate existing biases.

4 | CONCLUSIONS

Our multidisciplinary, patient-centered approach that leverages modern informatics tools will create opportunities to better triage patients, choose the best interventions, and target underlying determinants of disease. Targeted research that captures, quantifies, and analyzes social and environmental determinants of disease alongside clinical outcomes will be the key to developing interventions that lead to real-world change.[5,26,27] While ours is only one approach toward addressing asthma disparities, it highlights the need for additional social and environmental policies and interventions to address inequalities in asthma, and many other diseases in children.

AUTHOR CONTRIBUTIONS

Dr. Danica Liberman conceived and drafted the manuscript and reviewed and revised the manuscript. Drs. Jonathan Tam, Anna Cushing, and Juan Espinoza critically reviewed the manuscript for important intellectual content, made revisions, and drafted sections of the manuscript. All authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

ACKNOWLEDGMENTS

The work described here was supported by grants UL1TR001855 and UL1TR000130 from the National Center for Advancing Translational Science (NCATS) of the U.S. National Institutes of Health. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ORCID

Danica B. Liberman MD, MPH https://orcid.org/0000-0001-7626-2160

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Liberman DB, Tam JS, Cushing AM, Espinoza J. A novel tool using social and environmental determinants of health to assess pediatric asthma in the emergency department. *JACEP Open*. 2024;5:e13240. https://doi.org/10.1002/emp2.13240