This is a “preproof” accepted article for *Journal of Clinical and Translational Science*.
This version may be subject to change during the production process.
10.1017/cts.2024.500

The Health Equity Explorer: An open-source resource for distributed health equity visualization and research across common data models

William G. Adams, MD[1,2] *, Sarah Gasman, MS[1], Ariel L. Beccia, PhD[3], Liza Fuentes, DPH[4]

[1]Department of Pediatrics, Boston Medical Center
[2]Boston University Clinical and Translational Science Institute, Chobanian & Avedisian School of Medicine, Boston, MA
[3]Boston Children’s Hospital and Department of Pediatrics, Harvard Medical School, Boston, MA
[4]Health Equity Accelerator, Boston Medical Center, Boston, MA

***Corresponding author:** Address: 801 Albany St, Rm 2032, Boston, MA 02118., Cell phone: 508-400-5921. Email: badams@bu.edu

Abstract

Introduction: There is an urgent need to address pervasive inequities in health and healthcare in the US. [1,2] Many areas of health inequity are well known but there remain important unexplored areas, and for many populations in the US, accessing data to visualize and monitor health equity is difficult.

Methods: We describe the development and evaluation of an open-source, R-Shiny application, the "Health Equity Explorer (H2E)", designed to enable users to explore health equity data in a way that can be easily shared within and across Common Data Models (CDM).

Results: We have developed a novel, scalable informatics tool to explore a wide-variety of drivers of health, including patient-reported Social Determinants of Health (SDoH), using data in an OMOP CDM research data repository in a way that can be easily shared. We describe our development process, data schema, potential use cases, and pilot data for 705,686 people who attended our health system at least once since 2016. For this group, 996,382 unique observations for questions related to food and housing security were available for 324,630 patients (at least one answer for all 46% of patients) with 65,152 (20.1% of patients with at least one visit and answer) reporting food or housing insecurity at least once.

Conclusions: H2E can be used to support dynamic and interactive explorations that include rich social and environmental data. The tool can support multiple CDMs and has the potential to support distributed health equity research and intervention on a national scale.

https://doi.org/10.1017/cts.2024.500 Published online by Cambridge University Press

Introduction: There is an urgent need to address pervasive inequities in health and healthcare in the US. [1,2] Many areas of health inequity, particularly those affecting Black, Indigenous, and people of color are well known and well described.[3-8] However, there remain important unexplored area of health equity and for many populations in the US , accessing data to visualize and monitor health equity is difficult , despite an exponential increase in data from electronic health records (EHR). Furthermore, for institutions that offer tools for self-service data inquiry, the tools typically only support queries at a high level, for a single variable such as race, ethnicity, or sex. These systems also require training and expertise and are generally not accessible to community members due to privacy concerns.

Accurate assessment of health equity requires secure, accessible, reliable data and analytic code. Translational informatics innovation has led to broad adoption of “common data models (CDM)” such as the “Informatics for Integrating Biology with the Bedside (i2b2)”, “Observational Medical Outcomes Partnership (OMOP)”, and “National Patient-Centered Clinical Research Network (PCORNet)” CDMs [9,10] which has dramatically improved access to de-identified, standardized representations of EHR data for research and evaluation on a national scale. A growing number of institutions (including the one featured in this report) are also now routinely assessing social determinants (drivers) of health (SDoH)(e.g., food insecurity, housing insecurity, and economic instability) during clinical visits and recording responses in the EHR.[11] These sites are able to integrate these patient-reported SDoH data elements into their CDMs to make them available for research.[11-18] SDoH features related to where patients live are also increasingly available for use in systems that can link addresses reported at the time of visits to publicly available “place-based” (geo-spatial) social and environmental data at multiple levels (i.e., address, block, block group, census tract, census block, zip code, and state).

Complementing development of CDMs and expanded SDoH data at the person- and place-level, has been development of well specified and validated measures of health and healthcare processes and outcomes. Led by the US Centers for Medicare and Medicaid, these standard measures support the accurate and reproducible computation of health outcome status using electronic health data.[19] Electronic clinical quality measures (eCQMs) are “measures specified in a standard electronic format that use data electronically extracted from electronic health records (EHR) and/or health information technology (IT) systems to measure the quality of health care

https://doi.org/10.1017/cts.2024.500 Published online by Cambridge University Press

provided."[20] eCQM are routinely used within healthcare settings across the US, however, their use in research settings has been more limited. Their use is expected to grow with increased use of Fast Healthcare Interoperable Resources (FHIR) and development of FHIR eCQM specifications.

In this report, we describe a project to build an open-source, R-Shiny application, the "Health Equity Explorer (H2E)", designed to enable users to explore health equity data in an interactive way by building graphs, tables, and maps and conducting statistical analyses in a way that can be easily shared within and across Common Data Model (CDM) using communities. We prioritized approaches that could be implemented by a wide variety of potential collaborators to support exploration of virtually any computable health outcome from a wide variety of health domains. For this paper we focus on patient reported SDoH. However, H2E supports a broad and scalable array of social, environmental, and clinical attributes. Also, the project described in this report used the OMOP CDM, but the underlying database for H2E (H2E DataMart) could be created from any CDM using analytic software code re-engineered to map to coding systems for that CDM.

Materials and Methods: This project is located at the largest SafetyNet hospital in New England, Boston Medical Center (BMC) and includes its affiliated federally qualified community health centers (FQHCs). The project is a collaboration between the BMC Health Equity Accelerator (HEA),[21] BMC Research Operations, and the Boston University Clinical and Translational Sciences Institute (BU-CTSI). Data for the project was obtained from an OMOP CDM repository, the "Boston Data for Equity (D4E) Platform." D4E includes non-narrative data available from the BMC Epic EHR (diagnoses, medications, procedures, labs, vitals, clinical observations, and visits) and will also include data from our partner FQHCs.

BMC is a national leader in routine assessment of SDoH during clinical encounters. In 2017, BMC developed a one-page SDoH screening tool, THRIVE, that uses a subset of 8 SDoH questions from national screening instruments[11] Most THRIVE questions use the same question text and answer choices as an existing national screener (PRAPARE, AHC). THRIVE includes graphics designed to improve readability and is shorter (one-page) than other screening instruments to optimize workflows Although THRIVE use is limited to BMC and a limited number of partner CHCs and Health Systems, it's adoption at other sites is growing and by reusing the same questions as those in other surveys is able to assess SDoH in a similar that is consistent with other instruments. THRIVE questions assess housing security, food security, financial stability (trouble paying for medications/utilities), transportation challenges, trouble caring for family members, employment/unemployment challenges, and desire for additional education. THRIVE data from the EHR are mapped to standard terminologies and stored within the D4E Datamart.[18]

H2E also supports integrated use of place-based SDoH attributes. During preparation and updates of D4E data, patient addresses are geocoded to the census and zip code level. Data for census-and zip code level "place-based" social and environmental drivers of health (e.g. Child Opportunity Index (COI), Social Vulnerability Index (SVI), American Community Survey (ACS)) for all census tracts in the U.S.[22-26] Data in D4E are a limited dataset (PHI limited to dates, zip codes, and census tracts).

Equity Dimensions and Equity Attributes: In H2E, health equity outcomes are referred to as "Equity Dimensions (Dimensions)" since not all the observations are health outcomes. Dimensions can be demographic features (e.g. percent of population by race, ethnicity, sex, or member of a special population), SDoH features (e.g. prevalence of food or housing insecurity), medical or behavioral health condition (e.g. prevalence of autism or anxiety/depression), or clinical quality measure (e.g. percent of patients with diabetes with controlled hemoglobin A1C). Dimension data are pre-computed and stored within the H2E Datamart in the "equity_dimension" table for each person and each year of eligibility. We selected an initial set of Dimensions that included children and adults and represented a diverse set of health domains including: Health Conditions, Prevention/Screening, Immunizations, Behavioral Health, SDoH, Demographics, and Disability (see Table 1).

In H2E, features that may be drivers or determinants of health are referred to as "Equity Attributes (Attribute)" and include: demographics (e.g. race, ethnicity), SDoH features, Dimensions, and place-based features (See Table 1). Attributes are pre-computed and stored in the H2E Datamart in the "demo_attribute" and "dim_attribute" tables. The "dim_attribute" table allows all Dimensions to be available as Attributes and is created via a a post-processing table pivot. In H2E features can function as both Dimension and Attribute. For example, "anxiety or depression diagnosis" can be a Dimension and "food insecurity" an Attribute in one analysis, and in a separate analysis, “anxiety or depression diagnosis” can be an Attribute and “control of hypertension” could be the Dimension.

Our goal with the initial set of Dimensions and Attributes was to demonstrate the feasibility of our approach and to build a framework that can support many more of each in the future. Table 1 describes domains, dimensions, measure specification location, and CDM source.

H2E Data: SQL code customized to the vocabularies of the target CDM are used to populate the H2E DataMart. Dimension and Attribute processing begins in a staging area. For each year and Dimension, all eligible patients are assigned a “status” (e.g. “controlled” or “uncontrolled” for diabetes) and a value (e.g. “secure”, “at risk”, or “insecure” for food insecurity). Dimensions are assessed one time per patient per year (with most recent values typically used). Logic considers timing of events for clinical and place-based variables to ensure that they are only included after a condition was diagnoses (for example, a patient with first diagnosis of diabetes in 2020 would only be considered to have the condition from on or after 2020) and when available are based on validated code sets and logic from CMS endorsed eCQMs.

After processing, data for each Dimension is consolidated in the H2E Datamart “equity_dimension” table along with supporting demographic tables. The H2E application only requires two tables: “person_data” and “fips_data.” The “person_data” table includes all patient-related data needed to generate Dimension and Attribute measures and links to the Federal Information Processing Standards (FIPS) codes of residence. The “fips_data” table includes FIPS code level data related to the census tract of residence. The current “person_data” table design was developed to support an earlier Tableau-based H2E and will be optimized in the coming year to reduce duplication and increase efficiencies. The two primary tables for H2E are database “views” (linked tables presented as a single table) (see Figure 1). The “dim_attributes” table is generated from the “equity_dimension” table via an SQL pivot script which allows the application to use any Dimension as an Attribute via a table linkage (SQL JOIN) (See Figure 1). For our pilot version of H2E we limited our place-based data to COI and SVI. The “fips_data” view was created via a join of SVI and COI data by FIPS code. FIPS data can easily be added to the “fips_data” View (Figure 2) as needed via a relational join to the FIPS column. Currently, one race, ethnicity and sex status are supported for each measurement year. In the coming year we will add support for multiple races. Attribute data are also available as filters in H2E (Figure 1).

H2E Application Development: We used an interactive design process with input from multiple stakeholders including leaders of the Boston Medical Center "Health Equity Accelerator", Community Advisory Boards (CAB), and expert users. We also used materials from the Observational Health Data Sciences and Informatics (OHDSI) Community, open source statistical and application development tools, and standard measure specifications and value sets for target outcome measures. The application was initially developed in Tableau during May 2022-March 2023 and was then transformed into an R-Shiny App between June and September 2023. We chose R-Shiny to support a much broader array of statistical functionality not possible in Tableau and to enable open-source sharing of our application in the future. The R-Shiny develop work was done in collaboration with Appsilon, LLC (www.appsilon.com) and the "Data for Good" Program.

Results

We have developed an open-source platform that integrates clinical and place-based SDoH data. As of December 15, 2023, H2E contains 8,478,301 rows of Dimension data for 705,686 people who attended BMC at least once since 2016 and met criteria for at least one Dimension. For this group, 996,382 unique observations for questions related to food and housing security were available for 324,630 patients with 65,152 (20.1% of those with at least one visit) of the patients reporting food or housing insecurity at least once.

Health Outcomes: In the Health Outcomes Section, users choose a Dimension, and then select Attributes to stratify the outcome and visualize it as a graph or a data table. For this paper we demonstrate this functionality using the example of control of hemoglobin A1C for patients with diabetes, stratified by race and sex, (see Figure 3). The population can be filtered by Attribute values, and by clicking the "missing" checkbox, the number and percent of patients where the Dimension was not assessed will be displayed so users can assess differences and biases in assessment rates (Figure 3). We also explored relationships between the results of behavioral health screening for children and adults and food security. The PSC-17 is a routine screening tool to assess internalizing, externalizing, and attentional issue in 6-12 year old children.[27-29] At BMC, the PSC-17 screener is given with a THRIVE form so results of screening for both

https://doi.org/10.1017/cts.2024.500 Published online by Cambridge University Press

instruments is often available. A score of less than 15 is considered "normal." The PHQ-9 is a routine screening for depression.[30] At BMC, the PHQ-9 is also often given with THRIVE. A score of less than 10 is considered "normal." As shown in Figure 4, food insecure children and adults were substantially less likely to have a normal PSC-17 or PHQ-9 result. The results shown were generated in less than 5 minutes.

Advanced Analytics: Dimensions and Attributes can be included in additional analyses in the Advanced Analytics Section for inclusion in uni- and multi-variable analyses using R Packages (Figure 5). Users can descriptively model relationships of health outcomes and predictor variables. The exploratory data analysis tab helps assess collinearity, distribution of data, and the individual association of a variable with a health outcome. Data are fit to a logistic regression model to predict the likelihood or odds of a patient meeting the chosen Dimension criterion for a given set of Attribute. Estimated Marginal Means (EMM) is used to calculate the average likelihood of a patient meeting the criteria for a given metric within different subgroups (by race, age, sex, etc.). EMM is calculated by taking the average of each group's predicted values after adjusting for the other variables in the model providing a more interpretable understanding of the results of a logistic regression analysis.

The modeling component of the application allows users to select which Attributes to include in the model and how to group the results. Running the model returns coefficients, confidence intervals, and metrics to assess model performance, like variance inflation factor. A simple example of advanced analytics evaluating the association of results of depression screening via the PHQ9, and sex and food security is shown in Figure 5. In this example, a score below 10 is a "normal" or subthreshold score so a higher proportion having a score below 10 is a positive outcome. In the example, women and food insecure respondents were significantly less likely to have a score less than 10.

Geo-spatial visualization. In the "Neighborhood Maps" Section, users can explore visualizations of Dimension by census tract and simultaneously view place-based features from the list of SVI and COI reference data by census tract. Users can then select the "bivariate" checkbox to layer the two views to visualize the additive effect of the two features. The current H2E data model can support place-based data at the zip code, census tract, county and state. In the future, the functionality in this section will be expanded to support all these visualizations and will also be expanded to allow users to see much more detailed information about each area of interest. A simple example of a place-based visualization of blood pressure for patients with hypertension and SVI socioeconomic status is shown in Figure 6.

Discussion

In this report we describe a process, application design, and provide pilot data. Our primary goal was to demonstrate the functionality and potential uses for H2E, especially in the area of assessing patient reported and place-based SDoH. Our experience to date shows that data for a diverse set of health equity dimensions and attributes can be generated for children and adults using a common data model and shareable code. Since December 2023, we have already added over 400 additional place-based attributes and are able to develop and validate new Dimensions in several days. At our site, we are hosting H2E on a server located within the hospital intranet. Our plan over the coming year is to offer access to users with access to our other translational informatics resources (TriNetX, OMOP, i2b2, PCORNet). Our experience shows that with a tool like H2E, the data are easily explored in an interactive way as graphs, tables, statistical analyses, and maps in a way that allows dynamic exploration of the role of patient reported as well as place-based social and environmental drivers of health.

Advancing health equity is a national priority and the fundamental causes of health inequity, such as racism, are increasingly being recognized as public health crises.[31] H2E is a platform that most sites with a CDM could implement and use with existing staff and expertise. For OMOP-based settings, our SQL scripts could be used directly. For other CDM sites, reverse-engineering our OMOP scripts with mappings to concepts within i2b2 or PCORNet would be relatively easy, and with shared code libraries, the scripts could be shared. In this way, the underlying data for H2E could be generated from virtually any clinical data source and could potentially serve as a standard way to share “health equity” insight between different CDM using communities.

We acknowledge that data visualization and analytics in isolation will do little to advance health equity, however, we hope that tools like H2E can “shine a light” on inequity and identify “bright spots” that could be used to potentially identify solutions. We envision multiple potential use cases for H2E.

One potential use case would be for research users on institutional level to perform self-service exploration on-site using H2E hosted on an internal “Proxy” server (as at the site of this project). In this way, a large number of research users could explore existing equity dimensions quickly to prepare for research proposal submission. New Dimensions could also be added quickly and then explored immediately by the full range of already computed Attributes. The benefits of this case would be to generate new projects and proposals and monitor improvement activities related to hatchback health equity moving forward.

A second potential use case would be collaboration with public health leaderships at a city or state level. Sites with an existing CDM could share aggregate findings easily or use privacy preserving record linkages to link records across the city/state to study health equity in locations with multiple care sites. Results could be used to inform health and policymakers and evaluate community-based interventions such as those targeting economic mobility and housing in neighborhoods.

A third potential use case could be as a patient engagement tool. Patients could work with community advisory boards to identify priority conditions and then develop new Dimensions informed by the community to explore health equity at a neighborhood level. Such an approach could help engage patients in the research process and stimulate conversations leading to new promising research activities.

D2E could also be used within a National Health Equity Research Network between CTSA's and other research institutions with established CDM data. These centers are well prepared to add place-based data to their data models (if not already present) and with a library of shared analytic code tailored to each CDM, the effort required would be relatively small. Such a collaboration could start small but would be expected to grow quickly. Data sharing at this level would have great potential to support comparative health equity research on a national scale.

H2E is also well suited to education, training, and research applications. A wide range of potential users could be supported in a hands-on way that brings together geospatial and clinical data to evaluate equity in their community. We plan to extend the H2E Advanced Analytics Module to include new modules related to machine learning this year. Developers and data scientists could also use the open-source H2Eplatform to build new applications that leverage existing R packages. Lastly, the underlying data for H2E can easily be linked to the source CDM

https://doi.org/10.1017/cts.2024.500 Published online by Cambridge University Press

to allow data scientist to use the precomputed H2E outcomes and the underlying CDM data to support advanced data science applications. Clearly the benefits of this could potentially lead to accelerated workforce development, multi stakeholder engagement and new opportunities in data science.

Limitations: H2E provides easy access to detailed descriptive analyses, however, there are well known limitations of using EHR data and in most cases, additional analyses will be required to validate findings observed in H2E. Users of H2E will continue to need to have training in health equity and health services research. Analyses using H2E should be considered exploratory and best used for signal detection and hypothesis generation, since prediction modeling generally requires a specific set of methods that go beyond what is included in the tools. In addition, users are urged to not draw overly strong conclusions from results and to not use these results in ways that generalize, essentialize or stereotype certain groups. H2E should be used alongside other sources of evidence if guiding interventions.

An additional limitation is that the THRIVE instrument is currently only used at a small number of clinical sites and that as a safety-net hospital system, our results may not be generalizable to other sites. Even in our health system that has placed a very high priority on screening for SDoH screening, assessment is not universal. Unfortunately, most sites in the US do not currently screen for SDoH. However, it should be noted that H2E is not limited to, nor does it require patient reported SDoH data to provide rich insights and analyses related to health equity. All systems with CDMs have access to rich clinical and demographic data, and the addition of place-based data is feasible for many sites. While we hope that more health systems will be routinely asking patients about their SDoH experience soon, for sites that do not, tools like H2E could still offer value and insights.

Conclusion: The Health Equity Explorer can be used to support dynamic and interactive explorations of the diverse drivers of health and health inequity as graphs, tabular data, statistical analyses, and maps. The system has the potential to support multiple common data models and many more health equity dimensions and attributes in the future. With expanded use and partnerships, these tools have the potential to support distributed health equity research and intervention on a national scale.

Table 1. H2E Pilot Equity Dimension, Attributes, and CDM Table Sources

Equity Dimension Measure Set (status based on most recent data from each reference year)			
Category	**Equity Dimension**	**Measure Specification**	**CDM Source**
Health Conditions	Blood pressure control for patients with hypertension	Patients 18 - 85 years of age who had a diagnosis of hypertension and whose blood pressure was adequately controlled (< 140/90 mmHg) during the measurement period (NQF 0018)	Measurements, Conditions
	HgbA1C control for patients with diabetes	Patients 18-75 years of age with diabetes who had hemoglobin A1c < 9.0% during the measurement period (NQF 0059)	Measurements, Conditions
	BMI < 30	Patients ages 18 and above who have a Body Mass Index (BMI) below 30	
Prevention and Screening	Colon Cancer Screening	Patients 45-75 years of age who had recommended screening for colorectal cancer (NQF 0034)	Procedures
	Breast Cancer Screening	Women 50 - 74 years of age who had a mammogram to screen for breast cancer in the 27 months prior to the end of the measurement period (NQF 2372)	Procedures
	Tobacco Use	Patients who identify as non-smokers of those assessed for tobacco use	Observations
Immunization	COVID Immunization - Adult	Patients over 18 with one or more COVID vaccination record in year	Drug Exposures
	COVID Immunization - Children	Children 2-18 years old with one or more COVID vaccination record in year	Drug Exposures
Behavioral Health	Anxiety and Depression	Patients with diagnosis consistent with anxiety/depression during the 24 months prior to end of measurement year	Conditions
	Substance Use Disorder	Patients with diagnosis consistent with substance use disorder during the 24 months prior to end of measurement year	
	PHQ9 Score	Patients ages 12 and above who scored below 10 on all PHQ-9 screenings completed during year	Observations
	PSC-17 Score(s)	Children age 6 to 12 who scored below 15 overall, below 5 on internalizing section, below 7 on externalizing, below 7 on attention on PSC17 screening	Observations
Patient-Reported SDoH	Food Security	Patients who completed a THRIVE screening and who reported secure housing during the 24 months prior to end of measurement year	Observations
	Housing Security	Patients who completed a THRIVE screening and who reported secure access to food during the 24 months prior to end of measurement year	Observations
Patient features	Primary Care Patient	Patients with a primary care visit in current or previous year	Visits
	Autism	Patients with any ASD diagnosis	Conditions
	Disability-Vision	Patients with diagnosis consistent with bilateral blindness during or before measurement year	Conditions
	Disability-Hearing	Patients with diagnosis consistent with bilateral deafness during or before measurement year	Conditions

Equity Attributes	
Category	**Attributes**
Demographic	Race, Ethnicity, Sex, Gender, Primary Care Status
Clinical	All Equity Dimensions can be used
Place-based	Location history at census level (SVI, COI, and AHRQ SDoH (5 yr)} and zip code (AHRQ SDOH)

Note: Race and ethnicity are used in our analyses based on availability within our EHRs. We consider these features to be social constructs that reflect unmeasured factors related to individual and structural racism, racialization, and experiences of discrimination.

https://doi.org/10.1017/cts.2024.500 Published online by Cambridge University Press

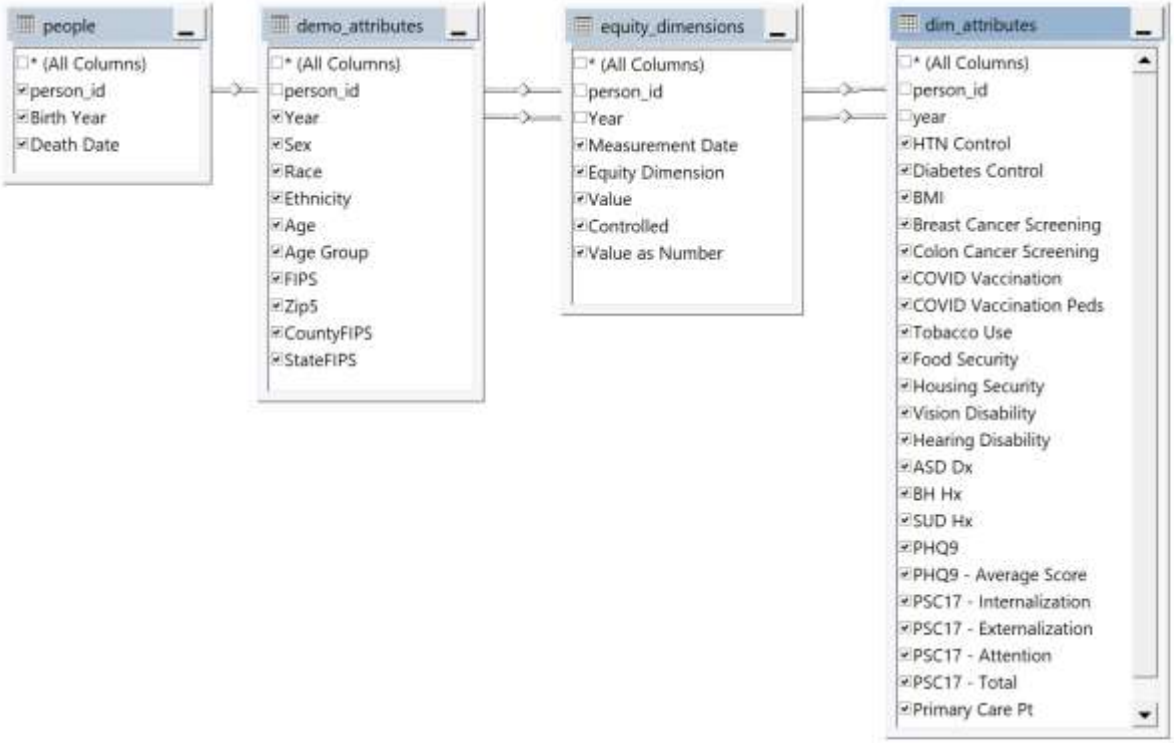


Figure 1: "person_data" View

Notes:

1. "dim_attribute" table is a dynamic pivot table of "equity_dimensions" table.
2. FIPS – Federal Information Processing Standards, ASD – Autism Spectrum Disorder, Dx – Diagnosis, BH – Behavioral Health, Hx – History, SUD – Substance Use Disorder, PHQ – Patient Health Questionnaire, Pt - Patient

:

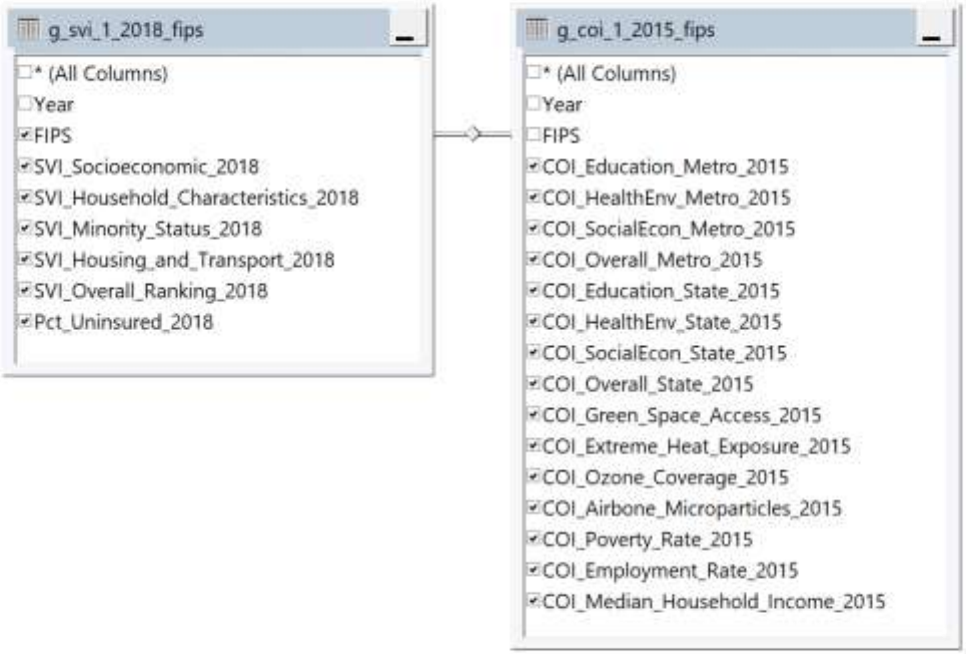


Figure 2: "fips_data" Database View

Notes:

1. Additional place-based data is added via join to "FIPS" column.

2. FIPS – Federal Information Processing Standards, SVI – Social Vulnerability Index, COI – Child Opportunity Index

https://doi.org/10.1017/cts.2024.500 Published online by Cambridge University Press

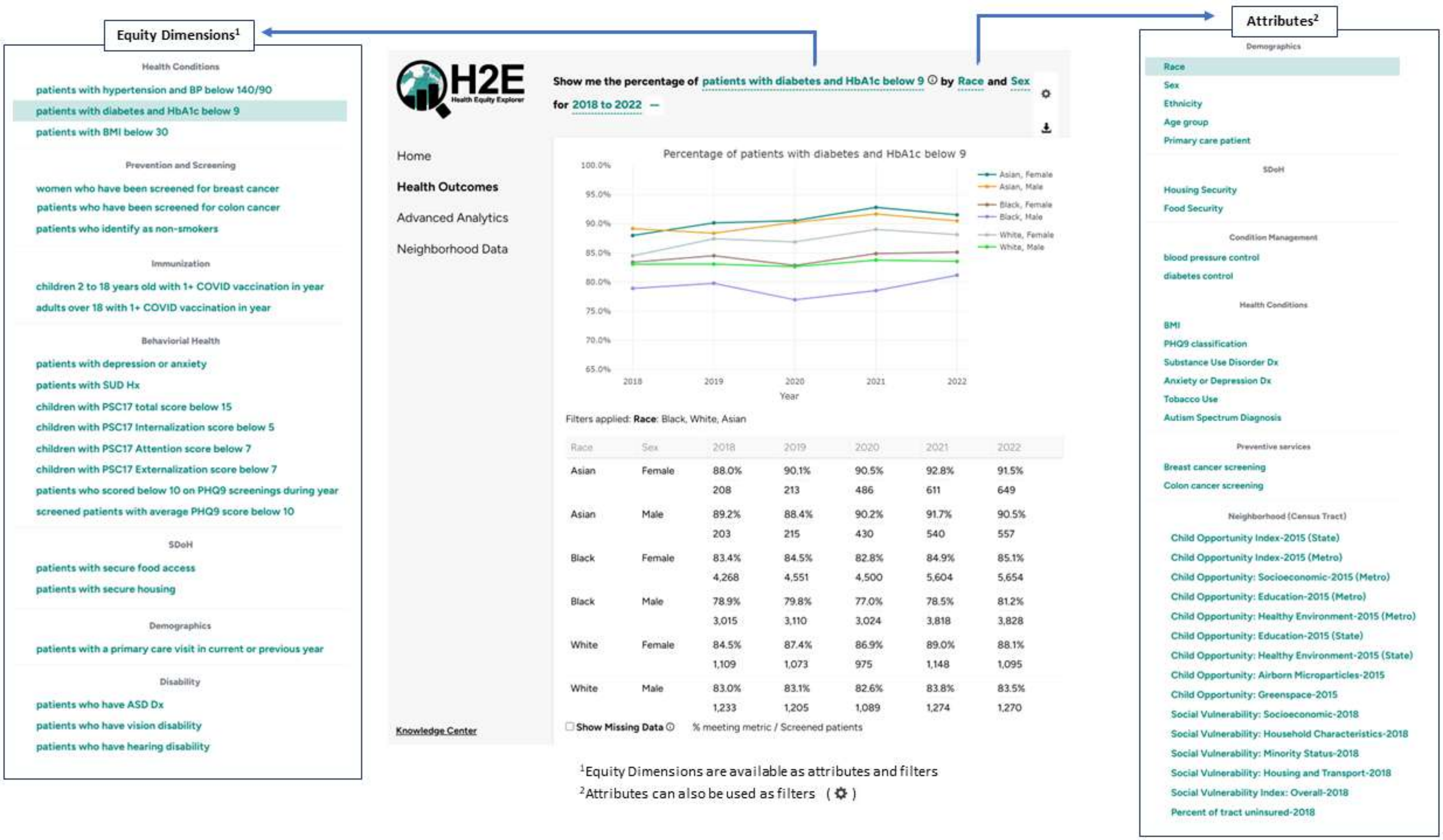
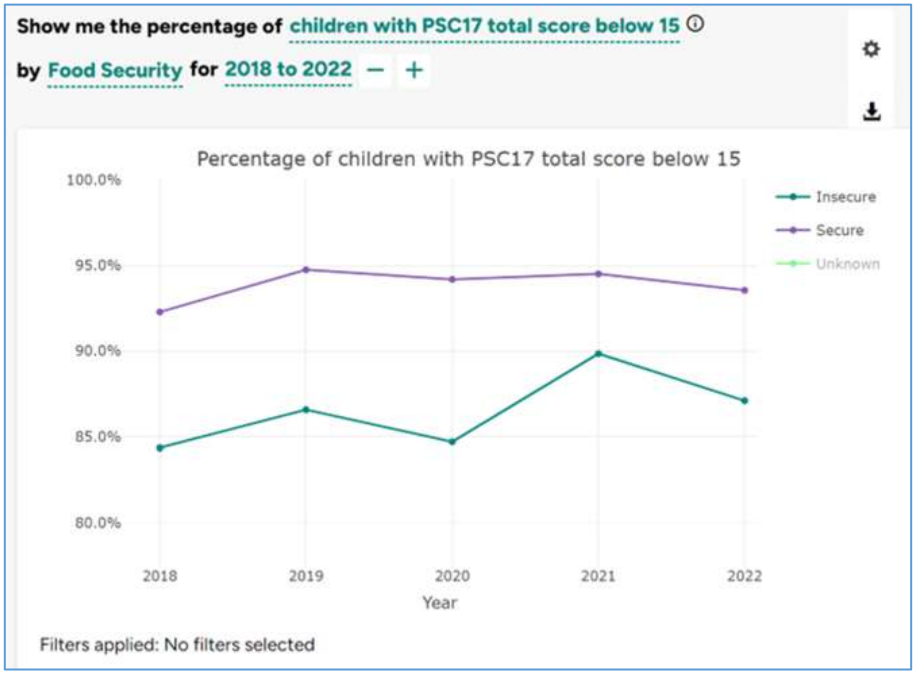


Figure 3. Health Outcomes Tab: Diabetes Control by Race and Sex



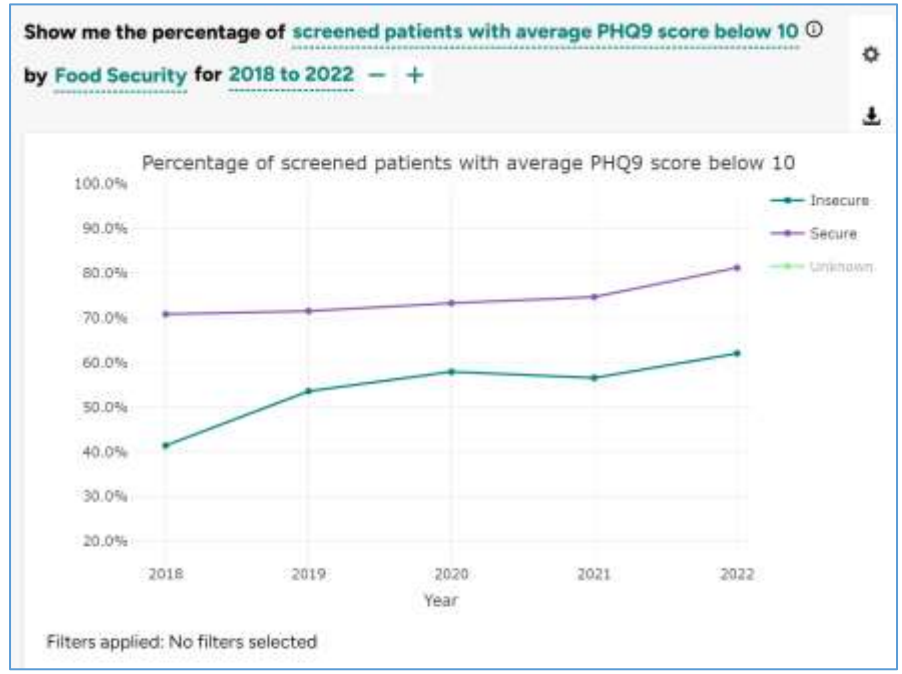


Figure 4. Pediatric Symptom Checklist (PSC-17) and Depression (PHQ-9) “Normal” Screening Rates for Food Security Subgroups

https://doi.org/10.1017/cts.2024.500 Published online by Cambridge University Press

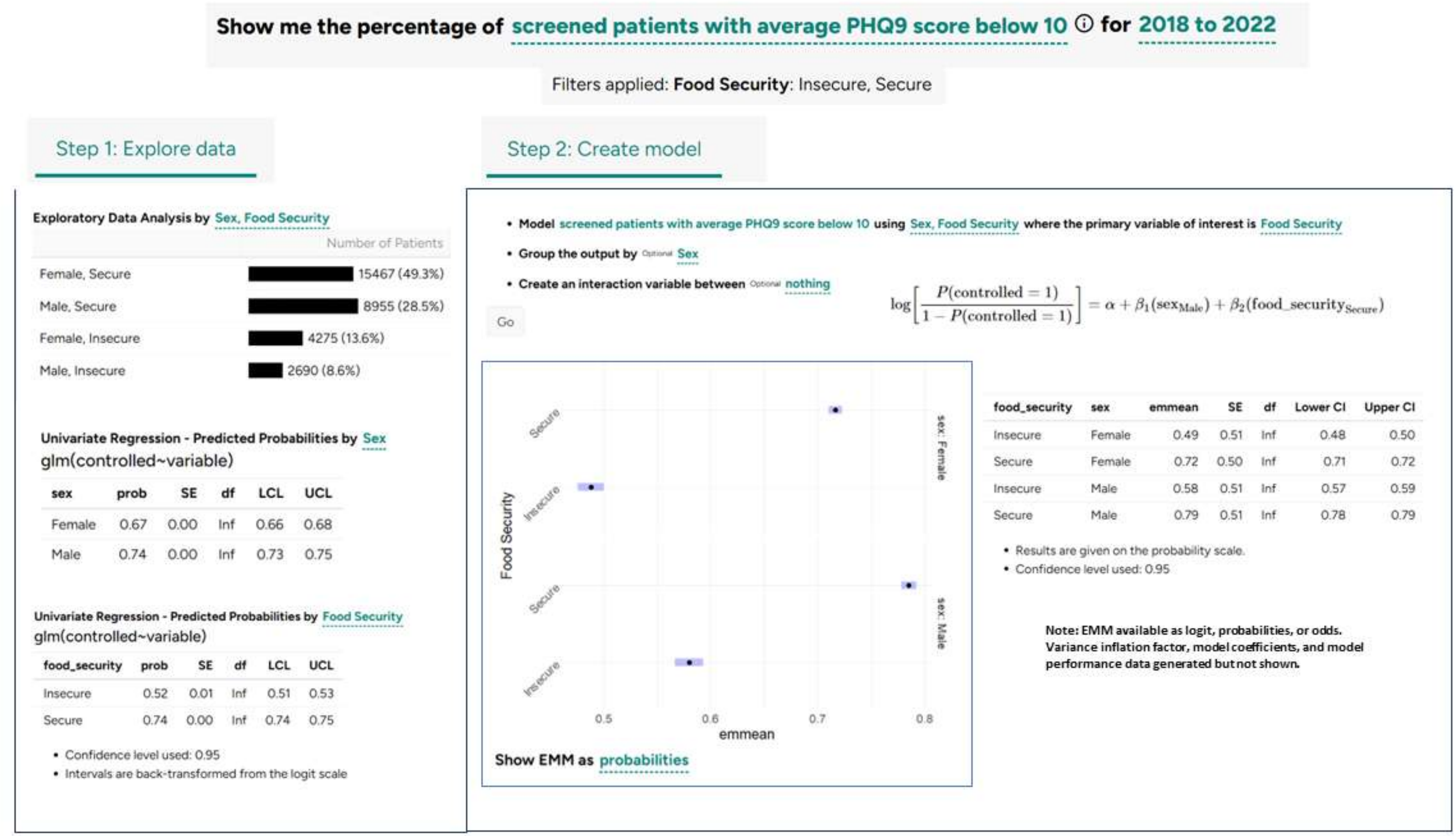


Figure 5. Advanced Analytics Tab: Evaluation of "Normal" PHQ-9 by Sex and Food Security

https://doi.org/10.1017/cts.2024.500 Published online by Cambridge University Press

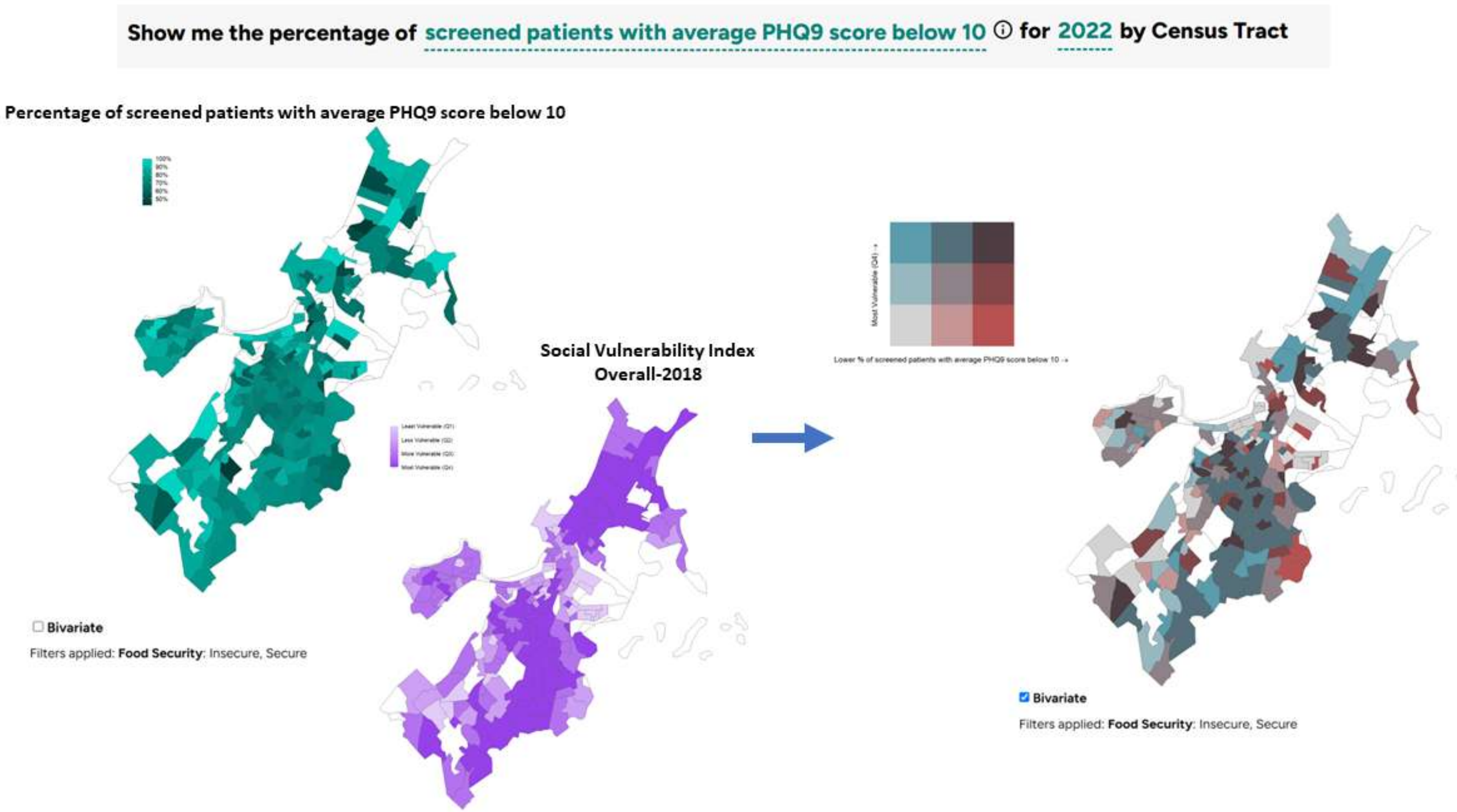


Figure 6. Neighborhood Data Tab: Comparison of Rates of "Normal" PHQ-9 by Census Tract and SVI Score

Acknowledgments: The authors would like to acknowledge and thank: 1) Ravin Davidoff, MD, Elena Mendez-Escobar, PhD, MBA and Megan Bair-Merritt, MD, MSCE for their support and leadership through the BMCHS Health Equity Accelerator over the past two years; 2) our colleagues from the National Covid Cohort Collaboration (N3C) Social Determinants of Health Workgroup for their pilot evaluation and enhancement suggestions: Charisse Madlock-Brown, PhD, Anthony Solomonides, PhD, MSc, MSc, and Juan Espinoza, MD; and 3) the project team from Appsilon: Ian E. Moore, Andrzej Białaś, Jakub Stępniak, Michał Parkoła , Yury Pribysh and Can Taşlıçukur.

Disclosures: The authors have no conflicts of interest to disclose.

Financial Support: This project was supported by the Boston Medical Center Health Equity Accelerator and National Center for Advancing Translational Sciences (1UL1TR001430)

Author Contributions: All four authors participated in the conception and design of the work. Dr Adams and Ms, Gasman participated in the collection and management of data. All four authors participated in the creation and evaluation of the software and tools, conduct and interpretation of analysis, and drafting of the manuscript. Dr Adams takes responsibility for the manuscript as a whole.

References:

1. *Healthy People 2020: Disparities*. US Department of Health and Human Services; 2019. Accessed December 9, 2023. https://www.healthypeople.gov/2020/about/foundation-health-measures/Disparities

2. Braveman P, Arkin E, Orleans T, Proctor D, A. P. What is health equity? And what difference does a definition make? Robert Wood Johnson Foundation; 2017. https://www.rwjf.org/en/library/research/2017/05/what-is-health-equity-.html

3. Institute of Medicine. Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care. In: Smedley BD, Stith AY, Nelson AR, eds. 2003.

4. Homan P, Brown TH, King B. Structural Intersectionality as a New Direction for Health Disparities Research. *J Health Soc Behav*. Sep 2021;62(3):350-370. doi:10.1177/00221465211032947

5. Adkins-Jackson PB, Chantarat T, Bailey ZD, Ponce NA. Measuring Structural Racism: A Guide for Epidemiologists and Other Health Researchers. *Am J Epidemiol*. Mar 24 2022;191(4):539-547. doi:10.1093/aje/kwab239

6. Lesko CR, Fox MP, Edwards JK. A Framework for Descriptive Epidemiology. *Am J Epidemiol*. Nov 19 2022;191(12):2063-2070. doi:10.1093/aje/kwac115

7. NBER. National Bureau of Economic Research - Moving to Opportunity. Accessed 12/17/2023, 2023. https://opportunityinsights.org/neighborhoods/

8. Swope CB, Hernandez D. Housing as a determinant of health equity: A conceptual model. *Soc Sci Med*. Dec 2019;243:112571. doi:10.1016/j.socscimed.2019.112571

9. Murphy SN, Mendis ME, Berkowitz DA, Kohane I, Chueh HC. Integration of clinical and genetic data in the i2b2 architecture. *AMIA Annu Symp Proc*. 2006;2006:1040.

10. Forrest CB, McTigue KM, Hernandez AF, et al. PCORnet(R) 2020: current state, accomplishments, and future directions. *J Clin Epidemiol*. Jan 2021;129:60-67. doi:10.1016/j.jclinepi.2020.09.036

11. Buitron de la Vega P, Losi S, Sprague Martinez L, et al. Implementing an EHR-based Screening and Referral System to Address Social Determinants of Health in Primary Care. *Med Care*. Jun 2019;57 Suppl 6 Suppl 2:S133-S139. doi:10.1097/MLR.0000000000001029

https://doi.org/10.1017/cts.2024.500 Published online by Cambridge University Press

12. Byhoff E, Garg A, Pellicer M, et al. Provider and Staff Feedback on Screening for Social and Behavioral Determinants of Health for Pediatric Patients. *J Am Board Fam Med*. May-Jun 2019;32(3):297-306. doi:10.3122/jabfm.2019.03.180276

13. Cottrell EK, Dambrun K, Cowburn S, et al. Variation in Electronic Health Record Documentation of Social Determinants of Health Across a National Network of Community Health Centers. *Am J Prev Med*. Dec 2019;57(6 Suppl 1):S65-S73. doi:10.1016/j.amepre.2019.07.014

14. Garg A, Cull W, Olson L, et al. Screening and Referral for Low-Income Families' Social Determinants of Health by US Pediatricians. *Acad Pediatr*. Nov - Dec 2019;19(8):875-883. doi:10.1016/j.acap.2019.05.125

15. Garg A, Homer CJ, Dworkin PH. Addressing Social Determinants of Health: Challenges and Opportunities in a Value-Based Model. *Pediatrics*. Apr 2019;143(4)doi:10.1542/peds.2018-2355

16. Herrera CN, Brochier A, Pellicer M, Garg A, Drainoni ML. Implementing Social Determinants of Health Screening at Community Health Centers: Clinician and Staff Perspectives. *J Prim Care Community Health*. Jan-Dec 2019;10:2150132719887260. doi:10.1177/2150132719887260

17. Phuong J, Zampino E, Dobbins N, et al. Extracting Patient-level Social Determinants of Health into the OMOP Common Data Model. *AMIA Annu Symp Proc*. 2021;2021:989-998.

18. Phuong J, Hong S, Palchuk MB, et al. Advancing Interoperability of Patient-level Social Determinants of Health Data to Support COVID-19 Research. *AMIA Jt Summits Transl Sci Proc*. 2022;2022:396-405.

19. Schreiber M, Krauss D, Blake B, Boone E, Almonte R. Balancing value and burden: the Centers for Medicare & Medicaid Services electronic Clinical Quality Measure (eCQM) Strategy Project. *J Am Med Inform Assoc*. Oct 12 2021;28(11):2475-2482. doi:10.1093/jamia/ocab013

20. CMS. Electronic Clinical Quality Measures Basics. Accessed 12/15/2023, 2023. https://www.cms.gov/medicare/regulations-guidance/promoting-interoperability-programs/electronic-clinical-quality-measures-basics

21. BMC. Boston Medical Center Health Equity Accelerator. Accessed 12/15/2023, 2023. https://www.bmc.org/health-equity-accelerator

22. Cutter S, Boruff B, Shirley W. Social Vulnerability to Environmental Hazards. *SSQ*. 2003;84(2):242-261. doi:https://doi.org/10.1111/1540-6237.8402002

23. Acevedo-Garcia D, McArdle N, Hardy EF, et al. The child opportunity index: improving collaboration between community development and public health. *Health Aff (Millwood)*. Nov 2014;33(11):1948-57. doi:10.1377/hlthaff.2014.0679

24. Sanoussi Y, Ahinkorah BO, Banke-Thomas A, Yaya S. Assessing and decomposing inequality of opportunity in access to child health and nutrition in sub-Saharan Africa: evidence from three countries with low human development index. *Int J Equity Health*. Aug 25 2020;19(1):143. doi:10.1186/s12939-020-01258-5

25. Census U. American Community Survey (ACS). Accessed 12/15/2023, 2023. https://www.census.gov/programs-surveys/acs

26. Ferrara P, Cammisa I, Zona M, et al. Child Opportunity Index: A Multidimensional Indicator to Measure Neighborhood Conditions Influencing Children's Health. *J Pediatr*. Jan 2024;264:113649. doi:10.1016/j.jpeds.2023.113649

27. Jellinek MS, Murphy JM. Screening for psychosocial disorders in pediatric practice. *Am J Dis Child*. Nov 1988;142(11):1153-7. doi:10.1001/archpedi.1988.02150110031013

28. Jellinek MS, Murphy JM, Burns BJ. Brief psychosocial screening in outpatient pediatric practice. *J Pediatr*. Aug 1986;109(2):371-8. doi:10.1016/s0022-3476(86)80408-5

29. Jellinek MS, Murphy JM, Little M, Pagano ME, Comer DM, Kelleher KJ. Use of the Pediatric Symptom Checklist to screen for psychosocial problems in pediatric primary care: a national feasibility study. *Arch Pediatr Adolesc Med*. Mar 1999;153(3):254-60. doi:10.1001/archpedi.153.3.254

30. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: validity of a brief depression severity measure. *J Gen Intern Med*. Sep 2001;16(9):606-13. doi:10.1046/j.1525-1497.2001.016009606.x

31. APHA. Racism is a Public Health Crisis. APHA. Accessed December 17, 2023, 2023. https://www.apha.org/Topics-and-Issues/Racial-Equity/Racism-Declarations