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Urban HEART Detroit: the Application of a Health Equity Assessment Tool

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Abstract The Urban Health Assessment Response Tool (Urban HEART) was developed by the World Health Organization. In 2016, the Urban HEART was adapted and used by the Healthy Environments Partnership, a long-standing community-based participatory research partnership focused on addressing social determinants of health in Detroit, Michigan, to identify health equity gaps in the city. This paper uses the tool to: (1) examine the geographic distributions of key determinants of health in Detroit, across the five Urban HEART specified domains: *physical environment and infrastructure*, *social and human development*, *economics*, *governance*, and *population health*, and (2) determine whether these indicators are associated with the population health indicators at the neighborhood level. In addition to the Urban HEART matrix, we developed various tools including graphs and maps to further examine Detroit's health equity gaps. Although not required by Urban HEART, we statistically analyzed the associations between each indicator with the health outcomes. Our results showed that all the domains contained one or more indicators associated with one or more health outcomes, making this an effective tool to study health equity in Detroit. The Urban HEART Detroit project comes at a critical time where the nation is focusing on health equity and understanding underlying determinants of health inequities in urban areas. A tool like Urban HEART can help identify these areas for rapid intervention to prevent unnecessary burden from disease. We recommend the application of the Urban HEART, in active dialog with community groups, organizations, and leaders, to promote health equity.

Keywords Urban health · Health equity · Detroit · Population health · Community-based participatory research

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Introduction

Health equity gaps in Detroit city are an ongoing concern. Some residents experience limited access to resources such as healthcare and healthy foods [1], poor air quality [2], housing instability [3], and unemployment or underemployment [4]. Detroit's historical and contemporary contexts, socioeconomic and physical environment challenges, racial and ethnic diversity, and strong history of collaborative research between community and academic partners make it a compelling setting for the adaptation and implementation of the Urban Health Assessment Response Tool (Urban

HEART), developed by the World Health Organization (WHO) [5, 6]. In 2016, the Urban HEART was adapted and used by the Healthy Environments Partnership (HEP), a long-standing community-based participatory research (CBPR) partnership focused on social determinants of health in Detroit, to identify health equity gaps in Detroit [7]. The process used was documented in the first paper published in 2017 [8], while this second paper focuses on the quantitative findings from the application of Urban HEART.

Background

The Urban HEART was developed by the WHO to combine quantitative data with community knowledge to evaluate and prioritize urban health inequities [5, 6, 9]. The tool consists of six steps: (1) build an inclusive team, (2) define the local indicator set and benchmarks, (3) assemble relevant and valid data, (4) generate evidence, (5) assess and prioritize health equity gaps and gradients, and (6) identify the best responses. Findings are intended to provide governments, researchers, and community-based organizations with consistent information to inform decisions and ensure cities attend to equity across multiple health-related domains [6]. The Urban HEART focuses on five domains: *physical environment and infrastructure*, *social and human development*, *economics*, *governance*, and *population health*. Each domain includes indicators to measure existing disparities among neighborhoods and to identify gaps and relationships in and across the domains, to ultimately identify areas of concern across the city and to develop strategic actions [6].

Urban HEART Detroit

The Urban HEART was adapted and implemented in 2016 by the HEP. This CBPR partnership consists of community-based organizations, academic researchers, and health service providers, including: Chandler Park Conservancy, Detroit Health Department, Detroit Hispanic Development Corporation, Eastside Community Network, Friends of Parkside, Henry Ford Health System, University of Michigan School of Public Health, and community members-at-large. These organizations provide services and address social issues ranging from housing affordability, neighborhood stability, parks and recreational facilities, educational opportunities, immigration status, and access to and delivery of healthcare (www.hepdetroit.org). From 2015 to 2016, the HEP Steering Committee (HEP SC), made up of representatives from these organizations, met monthly to implement the Urban HEART steps. A detailed description about this process is found in the first paper of this series [8]. The purpose of this paper is to provide an in-depth understanding of the data analysis and the evidence generated (Step 4) to identify the key determinants driving health inequities in Detroit. The analysis presented here addresses the following research questions: (1) What is the geographic distribution of key determinants of health in Detroit across the five domains encompassed in Urban HEART? and (2) Which, if any, of these social, physical, governance, and economic indicators are associated with health outcomes at the neighborhood level?

Methods

Data Source

Data used for the Urban HEART Detroit analysis was derived from publicly available sources. The initial analysis used 2009–2013 data [8]. Subsequently, the analysis was updated with more recent data. Data was obtained from four primary sources: 2012–2016 American Community Survey (ACS) [10], 2014 National Air Toxics Assessment [11], 2016 Center for Disease Control and Prevention's (CDC's) 500 Cities dataset [12], and 2015–2017 Michigan Behavioral Risk Factor Surveillance System [13, 14]. Data was obtained at the metropolitan area, city, and census tract (CT) levels. CTs were used as a proxy for neighborhoods and were the finest spatial scale for which all data used in the analysis was available. CTs located within Hamtramck and Highland Park, two cities located within the Detroit city boundaries, were excluded. Additionally, 6 CTs were excluded due to small sample size (less than 100 residents), resulting in a total of 291 CTs used for Urban HEART Detroit.

Indicators

A total of 14 indicators across 5 domains were identified through dialog among members of the HEP SC. Details on the selection process for each indicator can be found in our prior publication [8]. Following discussion with the HEP SC, indicators often described in the literature as community deficits (e.g., % households in poverty) were reframed to be expressed in terms of community assets (e.g., % households over the poverty line), with the exception of PM diesel because of the nature of its measurement [8]. Table 1 presents each indicator, its corresponding domain, their source, year, and a short description.

Data Analyses

We examined the geographic distribution of key determinants of health in Detroit, across the five Urban HEART domains, by calculating the mean/median for each indicator for all CTs within Detroit and for all CTs in the DMA (Table 1). The DMA includes Wayne (the county in which Detroit is located), Macomb, and Oakland counties, which are immediately adjacent to the city of Detroit. Means/medians for the DMA include Detroit values. These benchmarks were used to examine whether the mean/median for each CT was equal to or above the DMA mean/median benchmark (level 1), lower than the DMA but equal to or above the city mean/median (level 2), or lower than the city mean/median (level 3). For example, the median housing value for Detroit was $41,000, while in the DMA it was $131,423. If a CT had a median value of $55,000, it would be considered at level 2, greater than the Detroit median, but lower than the DMA median. A color gradient from light (level 1) to dark (level 3) was used to identify the levels. In addition, the *total population* was included for each CT, also from the ACS. This is an important contextual indicator. For example, resource needs and allocation will differ for CTs with 200 residents compared to the ones with 3000 despite both having a 50% employed population.

A matrix was then created including all the indicators and their corresponding categorical values (e.g., 1, 2, or 3) for each of the 291 Detroit CTs. To capture the distribution of the CTs for each indicator across each of the benchmark categories, we calculated the percent of CTs that fell into each of the three levels.

We then developed maps to display the geographic distribution of each indicator within the five domains. Although this is not a necessary step outlined in Urban HEART, it has been an effective tool in contextualizing indicators geographically [15, 16].

We then conducted statistical analysis using Detroit CTs, to examine associations between each of the social, physical, governance, and economic indicators and the four health outcomes in the population health domain. This analysis extends beyond the Urban HEART processes. It allowed the partnership to examine the size and significance of associations between each indicator.

Given the small number of Detroit CTs whose indicators were above the DMA average (level 1), we collapsed levels 1 and 2 for the statistical models. Thus models were run using a dichotomized version of the CT indicators, with 1 = at or above the Detroit benchmark and 0 = below the Detroit benchmark. Dependent variables consisted of prevalence rates (percentages) for each health outcome (e.g., % of residents without disability, have good mental health, have no asthma, and not obese) used as continuous variables in the models.

Each model was constructed by regressing each of the health outcomes as prevalence rates on the dichotomized indicators (above or below city means/medians) within each of the domains. A total of sixteen models were created using multivariate linear regression models, controlling for the median age at the CT derived from the ACS. All indicators were included as independent predictors in each domain-specific model.

Results

Each of the indicators organized by the Urban HEART domain along with their corresponding mean percent or medians for Detroit and the DMA levels is presented in Table 2. These were obtained directly from the ACS.

With the exception of non-auto commuters, across all indicators, the average across Detroit CTs was lower than the average for CTs in the DMA.

Results addressing our first research question regarding the distribution of key indicators in each of the five domains are found in Figs. 1 and 2. These figures and values were derived from the matrix. The matrix, which shows the results for each of the 14 indicators across the 291 CTs, is included in the supplement section.

Figure 1 presents the percent distribution of Detroit CTs that fell within each benchmark level. For example, 57.04% of Detroit CTs had lower median housing values compared to the city's mean value of $41,000 (level 3), 37.91% had median housing values higher than the city but lower than the DMA's median of

Table 1 Description of the indicators, by domain, including their source and year

Indicator	Source & year	Description
Economic growth domain		
Housing value	ACS[a] 12–16	Median housing value derived by homeowner's estimates of their home value, including house and lot, mobile home, and lot or condominium unit. Although this does exclude housing values of renter properties, it provides an approximation that has been used to reflect neighborhood wealth, quality, and affordability (Mehdipanah 2017).
Homeownership	ACS 12–16	Percentage of houses occupied by owners derived from the total number of owner-occupied houses occupied divided by the total number of houses occupied (renters and owners).
Occupied housing	ACS 12–16	Percentage of occupied homes derived from the total number of occupied houses divided by all housing units (occupied and vacant).
Income	ACS 12–16	Median household income derived based on the distribution of the total number of households and the incomes of the householders and all other individuals 15 y and over in the household, whether related or not.
Employment	ACS 12–16	Percentage employed was derived from the total number of employed individuals divided by the total population in the labor force (employed and unemployed).
Social & human development domain		
High school education	ACS 12–16	Percentage with high school diploma was derived from the total number of individuals with a high school diploma divided by the total population.
Bachelor's degree	ACS 12–16	Percentage with bachelor's degree or more was derived from the total number of individuals with a bachelor's degree or more, by the total population.
Children living above poverty line	ACS 12–16	Nonpoverty status was determined by comparing the total family income with the poverty threshold relative to the family size and composition. Percentage of children living above poverty line was derived from the total number of children not in poverty divided by total of households with children.
Governance domain		
Healthcare status	ACS 12–16	Percentage with health insurance was derived by dividing the total number of adults with public or private insurance by the total adult population.
Physical environment and infrastructure domain		
Diesel PM	NATA[b] 2014	Diesel PM values were derived based on PM10 emissions from on-road and nonroad mobile sources burning diesel or residual fuels (US EPA 2015). The exposure measure consisted of estimated inhalation exposure concentrations of diesel PM modeled based on annual average ambient outdoor concentration, human activity patterns, demographic features, and microenvironmental factors (US EPA 2015).
Non-auto commuters	ACS 12–16	Percentage of non-auto commuters was derived by dividing the total number of non-auto commuters (walked, biked, or used public transportation) by the total population who commute for work to obtain the percentage.
Population health domain		
Not obese	CDC[c] 15–17	Percentage of adults (aged 18 and over) normal or overweight was derived by subtracting crude prevalence rates of individuals with obesity from 100.
Good mental health	CDC 15–17	Percentage of adults (aged 18 and over) reporting good mental health was derived by subtracting crude prevalence rates of individuals with poor mental health from 100.
No asthma	CDC 15–17	Percentage of adults (aged 18 and over) without asthma was derived by subtracting crude prevalence rates of individuals with asthma from 100.
Not disabled	ACS 12–16	Percentage of adults (aged 18 and over) without disability was derived by subtracting the total individuals aged 18–64 who did not report any difficulties with vision, hearing, ambulatory, cognitive, self-care, and independent living from the total population in the same age group.

[a] ACS, American Community Survey; [b] National Air Toxics Assessment; [c] Center for Disease Control and Prevention

$131,423 (level 2), and 5.05% had a median housing value above the DMA's median (level 1). For about three quarters of the indicators, more than 40% of CTs had means/median values that were below the Detroit

Table 2 Mean or median values at the CT-level for each indicator, by domain, for Detroit and the DMA

	Detroit mean or median	DMA mean or median
Economic growth		
Median house value (per $1000)	41.0	131.4
Mean % homeowners	48.1%	67.2%
Mean % occupied housing units	70.2%	88.0%
Median household income (per $1000)	26.3	53.3
Mean % employed	77.9%	90.6%
Social & human development		
Mean % with high school education	79.0%	88.8%
Mean % with a bachelor's degree or more	13.8%	30.1%
Mean % children living above poverty line	43.8%	75.0%
Governance		
% mean with healthcare	85.5%	91.2%
Physical environments & infrastructure		
Mean PM totals	0.325	0.269
Mean % non-auto commuters	13.1%	3.5%
Population health		
Mean % not obese	53.0%	69.0%
Mean % good mental health	82.0%	87.0%
Mean % no asthma		
Mean % not disabled	80.0%	85.8%

mean/median (level 3). For three indicators, percent homeowners, not obese, and good mental health, over 45% of CTs were below the DMA mean and equal to or above the Detroit mean (level 2). For one indicator, non-auto commuters, the city mean percent was greater than the DMA percent.

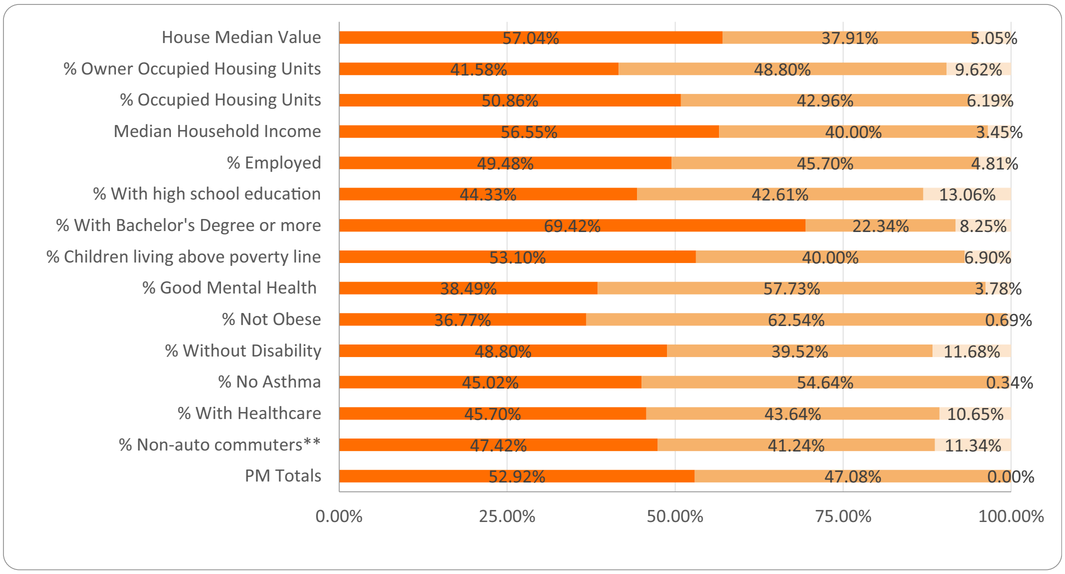

Fig. 1 The percent distribution of Detroit CTs based on their benchmark level for each of the indicators in the matrix. Level 1: equal or better than DMA; level 2: equal or better than Detroit but worse than DMA; level 3: worse than Detroit

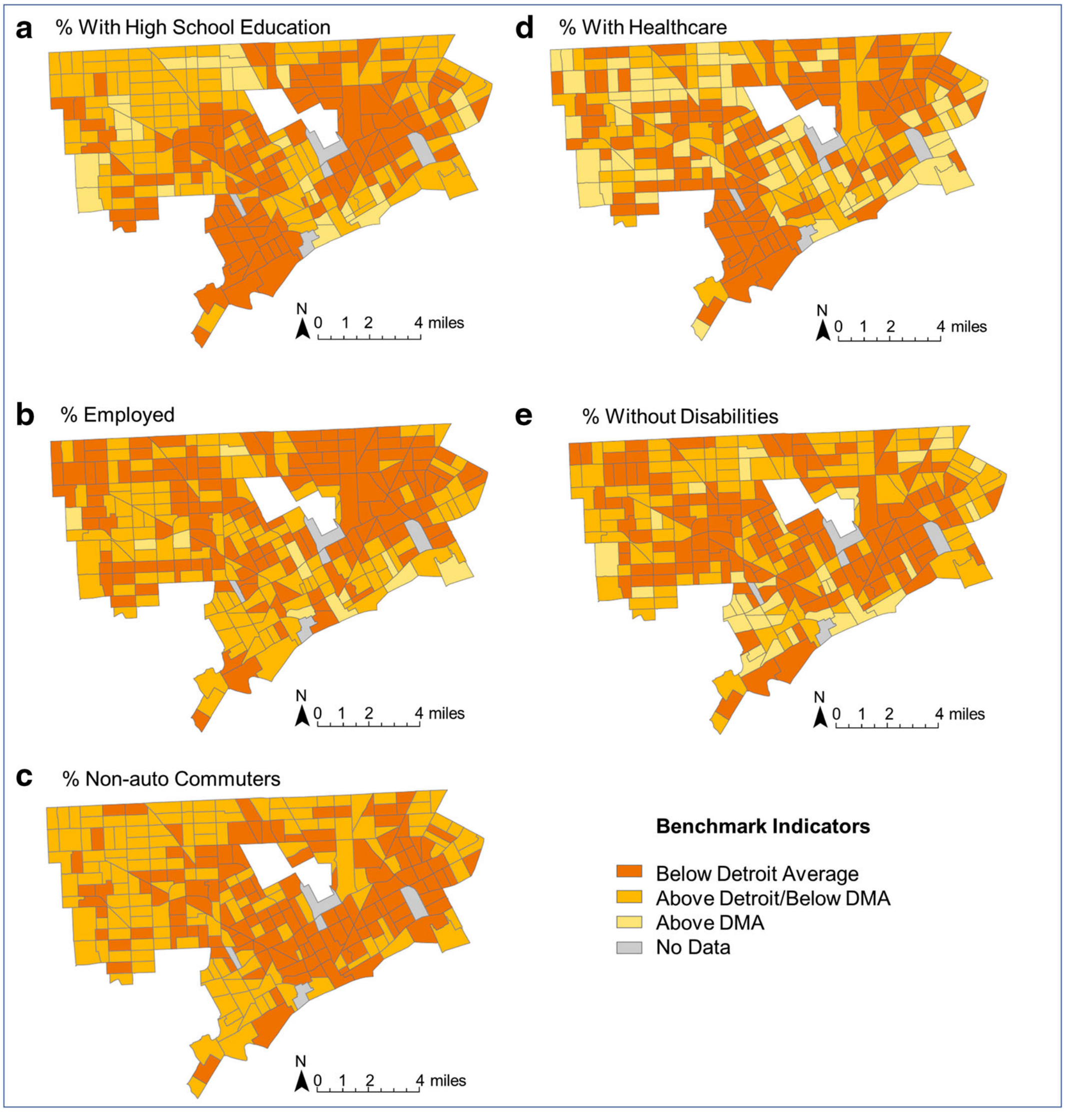

Fig. 2 Geographic distribution of high school education diploma, employment, non-auto commuter status, and without disability based on the Urban HEART benchmarks

Figure 2 shows the geographic distribution of one indicator selected for each of the five domains based on the three benchmark levels. These included % with high school diploma, % employed, % noncommuters, % with healthcare access, and % without disability.

Two larger clusters of CTs in the Southwest and Eastside of the city show lower levels of high school attainment compared to the city average (Fig. 2a). On the Westside, a cluster of CTs falls above the Detroit average but below the DMA average for the proportion of adults over the age of 24 with a high school diploma.

Figure 2b shows the distribution of employment rates across Detroit CTs, with areas with employment averages above those for the city but lower than the DMA scattered throughout the city. A cluster of CTs on the northeast side of the city has employment averages below the city average. In Fig. 2c, we show the distribution of non-auto methods of commuting (biking, walking, and public transportation) to and from work. In the center of the city, and toward the Eastside, there are clusters of CTs with averages of non-auto commuters lower than the city average.

In the governance domain, Fig. 2d shows the patterning of healthcare access (private or public). Patterns here are similar to those shown in Fig.2a (high school completion), with clusters of CTs on the Southwest and Eastside of the city having levels of healthcare coverage that are lower than the city average. By comparison, areas in Central and Southeast Detroit show health insurance coverage that is higher than Detroit averages and in some cases the DMA averages.

Finally, Fig. 2e shows the proportion of residents without disabilities. Clusters in the center of the city extending to the Westside and Eastside have shown rates below the city mean, while some CTs in the center and extending into Southwest show rates above the DMA averages.

Table 3 presents the results from regression models run to address our second research question: Which, if any, of these social, physical, governance, and economic indicators are associated with health outcomes at the neighborhood level? Models were run separately for each health outcomes and each of the domains with their corresponding indicators. Multicollinearity was not detected within any of the models.

Within the *economic growth* domain, CT rates of homeownership above the Detroit mean were associated with higher proportions with good mental health ($B = 0.005$, CI: 0.001, 0.010), with no significant association with disability, asthma, and obesity rates. CTs in which the percentage of occupied housing was at or above Detroit's mean had significantly higher proportions of residents with good mental health ($B = 0.006$, CI: 0.002, 0.011) and without disabilities ($B = 0.020$, CI: 0.008, 0.032), asthma ($B = 0.006$, CI: 0.003, 0.009), and obesity ($B = 0.022$, CI: 0.014, 0.030). In CTs with a higher median home value than Detroit's mean, similar trends were observed with significantly greater proportions of residents with good mental health ($B = 0.016$, CI: 0.011, 0.021) and without disability ($B = 0.015$, CI: 0.003, 0.027), asthma ($B = 0.003$, CI: 0.001, 0.006), and obesity ($B = 0.011$, CI: 0.003, 0.020). CTs with higher median household incomes than the Detroit's mean also had significantly higher proportions of residents with good mental health ($B = 0.017$, CI: 0.012, 0.022) and without disability ($B = 0.020$, CI: 0.008, 0.032), asthma ($B = 0.003$, CI: 0.011, 0.006), and obesity ($B = 0.018$, CI: 0.010, 0.027). Finally, CTs in which the percentage of employed residents was at or above the Detroit mean had significantly higher proportions of residents with good mental health ($B = 0.008$, CI: 0.003, 0.012) and without disabilities ($B = 0.019$, CI: 0.008, 0.031), asthma ($B = 0.008$, CI: 0.006, 0.011), and obesity ($B = 0.025$, CI: 0.017, 0.033).

For the *social and human development* domain, CTs with higher percentage of adults with high school diplomas compared to Detroit's mean had a greater proportion of residents with good mental health ($B = 0.022$, CI: 0.018, 0.026) and without disability ($B = 0.018$, CI: 0.006, 0.030) and no significant associations with asthma or obesity. CTs in which percent of residents with a minimum of a bachelor's degree was higher than Detroit's mean had a greater proportion of residents with good mental health ($B = 0.019$, CI: -0.023, -0.015) and without disabilities ($B = 0.027$, CI: 0.014, 0.041), asthma ($B = 0.009$, CI: 0.006, 0.012), and obesity ($B = 0.037$, CI: 0.027, 0.046). In CTs with a higher proportion of children living above the poverty line compared to Detroit's mean, a greater proportion of residents had good mental health ($B = 0.013$, CI: 0.009, 0.016) and no disability ($B = 0.021$, CI: 0.009, 0.033), asthma ($B = 0.005$, CI: 0.003, 0.008), and obesity ($B = 0.024$, CI: 0.016, 0.032).

Within the *governance* domain, CTs with a higher proportion of residents with health insurance than Detroit's mean had higher proportions of residents with good mental health ($B = 0.012$, CI: 0.007, 0.018), while there were no significant associations between health insurance and the proportion of residents without disability, asthma, or obesity.

In the *physical environment and infrastructure* domain, although CTs with higher PM diesel exposure levels compared to Detroit's mean trended toward a lowered proportion with good mental health and greater proportions with disabilities, asthma, and obesity, these trends were not statistically significant. In CTs with a greater percentage of residents who were non-auto commuters compared to Detroit's mean, a smaller proportion of residents reported good mental health ($B = -0.007$, CI: -0.013, -0.002), and a greater proportion were without asthma ($B = 0.003$, CI: 0.000, 0.006). There were no significant association between proportion of non-auto commuters and disability or obesity.

Discussion

The adaptation and implementation of the Urban HEART Detroit yielded a set of informative tools—matrix, distribution graphs, and maps—for researchers

Table 3 Models for health outcomes regressed on dichotomized indicators within each domain

	Not disabled		Good mental health		No asthma		Not obese	
	Coef. Est.	95% Conf. Int.	Coef. Est.	95% Conf. Int.	Coef. Est.	95% Conf. Int.	Coef. Est.	95% Conf. Int.
Economic growth								
Homeowners	0.011	−0.001, 0.022	0.005**	0.001, 0.010	0.002	−0.001, 0.004	0.003	−0.005, 0.012
Occupied housing	0.020**	0.008, 0.032	0.006**	0.002, 0.011	0.006**	0.003, 0.009	0.022***	0.014, 0.030
Median home value	0.015**	0.003, 0.027	0.016***	0.011, 0.021	0.003*	0.001, 0.006	0.011**	0.003, 0.020
Median household income	0.020**	0.008, 0.032	0.017***	0.012, 0.022	0.003*	0.001, 0.006	0.018***	0.010, 0.027
% employed	0.019***	0.008, 0.031	0.008***	0.003, 0.012	0.008***	0.006, 0.011	0.025***	0.017, 0.033
Social & human development								
With high school education	0.018**	0.006, 0.030	0.022***	0.018, 0.026	−0.000	−0.003, 0.003	0.006	−0.002, 0.015
With bachelor’s degree	0.027***	0.014, 0.041	0.019***	0.015, 0.024	0.009***	0.006, 0.012	0.037***	0.027, 0.046
Children living above poverty line	0.021***	0.009, 0.033	0.013***	0.009, 0.016	0.005***	0.003, 0.008	0.024***	0.016, 0.032
Governance								
With insurance	0.010	−0.003, 0.022	0.012***	0.007, 0.018	−0.001	−0.003, 0.002	0.008	−0.002, 0.017
Physical environment & infrastructure								
Diesel PM exposure totals	−0.001	−0.013, 0.012	−0.004	−0.010, 0.010	−0.002	−0.004, 0.001	−0.002	−0.012, 0.008
% non-auto ccommuters	−0.005	−0.018, 0.007	−0.007**	−0.013,-0.002	0.003*	0.000, 0.006	0.004	−0.005, 0.014

* $p < 0.05$, ** $p < 0.01$, and *** $p < .001$. All models were adjusted for mean age

and community organizations to highlight health equity gaps. Furthermore, although not a component of the Urban HEART process, findings from the statistical models suggest that several of the indicators selected for the matrix are appropriate for inclusion as determinants of health outcomes, while others may require further discussion on how results should be interpreted. Here, we discuss the findings in detail.

Urban HEART Application

The matrix (Supplement 1) provided the opportunity to examine patterning of CT-level indicators as they are distributed geographically (by column) or to examine the set of indicators relevant for a CT (by row). The matrix is helpful in showing patterns of CTs that are lower than the city average or higher than the DMA average. However, the 291 rows included (one for each CT) can make it difficult to navigate. Thus, we took two steps to help visualize and understand the large amount of data available when assessed at the CT, as was done for Detroit. First, summarizing the matrix by using a graph of the percent distribution of CTs for each of the indicators of the matrix (Fig. 1) offers a summary measure for the city's CTs across all the indicators while comparing to the DMA referent. Second, the maps created at the CT-level and presented in Fig. 2 allow a visual inspection of whether and how indicators may cluster or otherwise be distributed geographically within the city. Mapping at the relatively fine scale of CTs allows more nuanced insights into the geographic patterning of the indicators.

Community insights and knowledge of the historical and political context of the city were critical for interpretation of indicators and guided their applicability for policy decisions [8]. Understanding the patterns and dynamics that underlie the initial statistical analysis is critical to the Urban HEART process. The initial findings can signal areas for further dialog, opportunities to obtain insights from community members, and further research to develop adequate and appropriate recommendations for policies and interventions [8]. The indicator non-auto commuter is a good example of this where a greater proportion of CTs in the downtown and midtown areas use private vehicles to commute (Fig. 2). However, the midtown-downtown corridor also has some of the city's newer and more efficient public transportation available due to the recent addition of a light-rail and streetcar system. It is plausible that this finding instead reflects a larger percentage of the population of this area working in jobs beyond the downtown core. Further exploration, using ACS data, indicates that at least 20% of residents of the downtown and midtown areas commute more than 20 min per day [10]. These are also areas of higher income and therefore may have increased access to personal automobiles. Other areas of the city, including the Eastside, where there is a larger non-auto commuter population, also tend to have poorer and less-efficient public transportation and a population that heavily relies on public transportation for employment throughout and outside of the city [4, 17]. Together, these patterns suggest the complexity of interpreting the inverse association between the proportion of non-auto commuters and the proportion with good mental health.

Although not part of the process for the Urban HEART, our team conducted statistical analysis to determine associations in each domain and the four health outcomes in the population health domain. For this analysis we used only Detroit's CTs and not those in the broader DMA. This allowed us to examine the association between each of the indicators to the population health variables to determine if in fact they were significant predictors of health equity gaps in the city. Our findings showed that each of the selected indicators, with one exception, PM2.5, was associated with one or more of the health outcomes. These findings lend support to the adequacy of most of the indicators used to examine health inequities in Detroit. These findings also support existing place-based research looking at these factors separately including neighborhood social environments like income and education and poverty and their links to mental health [18], cardiovascular health [19], and mortality [20]. Similar studies looking at neighborhood physical environments have also linked air pollution and transportation to body mass index [21]. Although some studies have created neighborhood indices that consists of some of these indicators [22–24], for policy and program recommendations, information on independent indicators is important to determine focus and priority, especially when funding is limited.

The PM2.5 indicator was the only indicator not significantly associated with any of the study's health outcomes. This finding is inconsistent with prior research that has demonstrated areas of Detroit that experience excess exposure to PM2.5 with significant associations with health outcomes [2, 25]. The focus of this study only on CTs within the city of Detroit and the crude measure of PM2.5 used in this analysis (as higher or lower than the average DMA) likely contributed to the failure to finding significant associations with asthma, in contrast to substantial literature that used more precise measures of PM2.5 demonstrating significant association [26–28]. Furthermore, there is relatively little evidence and no clear pathway linking PM2.5 exposure with the other health outcomes used in this analysis: mental health, disability, and obesity [19–21]. Thus, we believe that the insignificant associations between PM2.5 and our health outcomes likely lie in the methods used, as well as the selection of health outcomes. It suggests limitations in using the Urban HEART process to quantify health impacts, rather than to classify areas, due to the loss of variability that occurs when data is collapsed into relatively crude categorical variables and when specific environmental indicators are used to predict health outcomes without established pathways.

The implementation of Urban HEART Detroit is a first step in measuring and examining various factors contributing to health inequities in the city. The Urban HEART can be applied to help identify and focus intervention and policy recommendations to prevent unnecessary health burden. In our first paper of this series, we provide an extensive discussion on the usage of these findings as part of the CBPR approach we took [8]. One area identified as a potential focus for continued research was addressing homeownership [29]. Since then, the HEP SC has been involved in two major programs focused on neighborhood predictors of housing discrimination in the city and surrounding areas [30] and on homeownership inequities associated with accessing and attaining poverty exemption on property taxes [3, 31]. Both studies have provided substantial evidence that has informed policy change in this area. The Urban HEART also continues to inform funding strategies aimed at showing the potential impacts future work can have in reducing health inequities in Detroit. While discussions have occurred with Detroit's Health Department about imbedding the Urban HEART analytic process within the organization, challenges in administration and priorities, especially given COVID-19, have interrupted those discussions. Results from the Urban HEART process described here continue to be overseen by the HEP SC and made available to both researchers and community organizations wishing to use it.

Despite Urban HEART's potential in monitoring health inequities within a city, there are some limitations in using this approach. To ensure access and sustainability of the tool, data is limited to those publicly available. The ACS and 500 Cities data, used here, are generally available with a one- to two-year delay resulting in potentially outdated data depending on the usage needs of the tool. However, closer collaboration with city departments, for example, the integration of the tool within the city's health department, could result in updated data from vital records and other sources, allowing a more refined analysis. Secondly, because of limited health data available prior to 2015 at the CT-level, past comparison of health status to determine any changes in the outcomes over time are not possible yet. As noted above, using CT-level data can lead to challenges in interpreting and seeing patterns across many geographic areas. Techniques for visualizing the distribution across geographic areas, such as mapping, may clarify the patterning of data. As presented here, the relatively refined geographic scale of CTs can be an asset in allowing the visualization of nuanced patterns at a fine spatial scale. CTs, as has been widely discussed in the literature, are a proxy for "neighborhoods," and the extent to which they map onto socially defined geographic areas that are meaningful for residents is a subject of debate [32–34]. Future research can consider whether there are other ways of classifying areas that may be more meaningful within the context of any given city, and if so, whether data are available aggregated to those geographic areas. Other data reduction efforts used here, such as collapsing data into categorical variables, had both strengths and weaknesses in the context of this analysis. A strength is that it allows a simple tool for capturing and classifying areas in terms of the immediate (e.g., Detroit) and more distal (e.g., DMA) geographic areas. A weakness when applying those classifications as predictors of health in multivariate models is that of compressed variance across areas which likely dampens the ability to identify multivariate associations with health. A possible result of this effect is that multivariate associations reported here are likely to be conservative. Future studies using Urban HEART and measuring its potential effects on policy and program interventions because of this process should consider longitudinal data to look at trends in health inequities to determine changes in outcomes and also whether more nuanced construction of predictor variables may be useful when modeling associations with health outcomes.

Conclusions

Extensive dialog within the HEP SC informed the selection of the indicators used for this analysis, their construction and scaling, and the interpretation of the results. The tool has helped in assessing indicators in the five domains across Detroit. It offered a first step in understanding variations in challenges and opportunities across areas of the city, including those requiring further investment.

The Urban HEART Detroit project comes at a critical time where the nation is focusing on health equity and understanding underlying key determinants of health inequities in urban areas. An examination of the patterning of social, physical, economic, and political determinants of health and their associations with health provides a powerful tool that can be used to visualize and quantitatively assess the drivers of adverse health outcomes and also to identify neighborhoods that may particularly benefit from specific types of investment to improve the health of their residents. We recommend the application of the Urban HEART, in active dialog with community groups, organizations, and leaders, as a tool to move forward analysis and action to address determinants of health and to promote health equity.

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