HEALTHY CORRIDOR INDEX 2.0

Technical Documentation

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1. Introduction

1.1. Background

Many government agencies and academic institutions have developed index tools to evaluate the opportunities or disadvantages of countries, cities, and regions. These tools typically include a variety of indicators that are grouped into common themes, and the selection of these indicators often reflects the interests and goals of the tool developers. These goals may include reducing poverty, promoting environmental equity, addressing climate issues, solving housing and transportation problems, reducing crime, and improving walkability. These indices provide policymakers with a measurable basis for allocating resources and actions to the areas of greatest need.

Some tools use a single metric to rank areas, such as the New York Vision Zero Priority Area, which ranks New York City's transportation priority areas based on traffic fatalities. Other indexes further group individual indicators into domains and use statistical methods to combine multiple domains into an overall score (with or without weighting). Detailed information about these indexes can be accessed through the links provided below.

- Virginia Health Opportunity Index (USA)
- ONS Health Index (UK)
- The California Healthy Places Index (USA)
- Area Deprivation Index (USA)
- US Opportunity Index (USA)
- Child Opportunity Index 2.0 (USA)
- The English Indices of Deprivation 2019 (UK)
- NYC Well-being Index (USA)
- CDC Social Vulnerability Index (USA)
- Smart Location Index (USA)

1.1.1. What are Social Determinants of Health?

According to the World Health Organization (WHO), Social determinants of health (SDOH) are the conditions in the environments where people are born, live, learn, work, play, worship, and age that affect a wide range of health, functioning, and quality-of-life outcomes and risks [1]. SDOH represents nonmedical factors — like housing, transportation, and poverty — that affect health. Differences in these conditions may put people at risk for poor health outcomes [2].

According to the program launched by the Centers for Disease Control and Prevention (CDC), Healthy People 2030 [3], and the domain framing of HCI 1.0. HCI 2.0 constitutes five domains: **Social and Economic, Education, Natural Environment, Neighborhood, and Transportation**

1.1.2. What is Health Corridor Index 2.0?

Urban corridors are streets that accommodate a variety of modes of transportation and uses, such as cars, bikes, buses, and pedestrians. These corridors may range in width from 2-6 lanes and typically feature sidewalks, bike lanes, transit stops, and on-street parking. Urban corridors often serve as major connectors for local and regional trips, and buildings are located along the sidewalk to create a street. People who live, work, and travel along these corridors rely on them for services and amenities to meet their daily needs. However, the built environment of these corridors, along with the rise of chronic diseases such as obesity, heart disease, diabetes, and asthma, and the increase in injury rates for pedestrians and bicyclists, highlights the need to consider how corridor redevelopment can foster healthier behaviors and lifestyles. To address these issues, the Urban Land Institute (ULI) has proposed a program to create healthy corridors across the United States. A healthy corridor is defined as an easily navigable and comfortable street with a visually appealing and active streetscape that protects road users, enhances neighborhood vitality, serves as a local community amenity, and increases accessibility and mobility by providing linkages to employment and services (such as education, health care, and recreation), offering transit options, and promoting sustainable transportation modes and physical activity [4].

The Health Corridor Index (HCI) 2.0 is a tool that measures the conditions of corridors that affect people's health, ranking corridor health scores across New York City (NYC). HCI 2.0 allows policymakers and urban planners to identify corridors that need prioritized short-term and long-term improvements to infrastructure, design, land use, public engagement, and programming in order to promote health.

HCI 2.0 is distinct from other health indices in that it focuses not only on macro factors such as socio-economic and environmental factors, but also pays more attention to the impact of the built environment on people's health. The index aims to quantify the impact of urban design elements (such as tree density, sidewalk width, and access to open space) on health outcomes. HCI 2.0 provides a quantitative foundation for urban designers to estimate the influence of urban design solutions on health outcomes.

HCI 2.0 is based on HCI 1.0, which was jointly developed with the DOT and the Design Trust for Public Space (Design Trust), and launched in 2020. HCI 1.0 included information on

21 indicators covering four domains of health (Figure 1-1). HCI 2.0 utilized new measures and methodologies. Table 1-1 outlines key differences between the two versions.

For HCI 2.0, we revisited the indicators and methods for constructing the index. HCI 1.0 used data at the Neighborhood Tabulation Areas (NTAs) level in NYC, while HCI 2.0 used data at the census tracts level, which is a more granular geographic unit. The HCI was constructed by computing the average score of geographic units in the corridor's proximity and then projecting it onto the target corridor, so more granular geographic unit data can capture more detailed information. In addition, we changed the methods for generating indicators into five domains and total scores. Each indicator and domain were weighted equally in HCI 1.0, while in HCI 2.0, each indicator is assigned an individual weight based on how well it predicts health outcomes.

Figure 1-1 HCI 1.0 Indicators and Domain

HCI 1.0	HCI 2.0
• 21 indicators	• 15 indicators
• Not include education indicators	• Include education indicators
• Include health outcome indicators	• Not include health outcome indicators
• NTAs level Data	• Census Tract level Data
• All indicators weighted equally when combined into the index	• Individual indicators are given weights based on how well they predict health outcomes.

Table 1-1 Key differences between HCI 1.0 and HCI 2.0

In the following sections, we will provide an overview of the 15 indicators included in the index for each of the five domains (**Social and Economic, Education, Natural Environment,**

Neighborhood, and Transportation) and explain the scientific reasoning for their inclusion. We will also discuss the methodology used for weighting and combining the indicators into the overall index. Finally, in the appendices, we will provide additional information on data sources and methodologies for constructing the indicators.

2. Domains and Indicators

2.1. Criteria for Domain and Indicator Selection

ULI proposes to build healthy corridors that should take into account the needs of surrounding neighborhoods, using a *healthy corridors* approach in corridor planning integrates topics of safety, accessibility, social cohesion, housing and transportation choice and affordability, environmental sustainability, and resilience [5]. HCI 2.0 selected indicators based on these principles:

- Following the framework of CDC Social Determinants of Health (Figure 2-1)[3]
- Data at the census tract level
- Accessible public data sources
- Association with Health outcomes
- Continuity with previous versions (HCI 1.0)

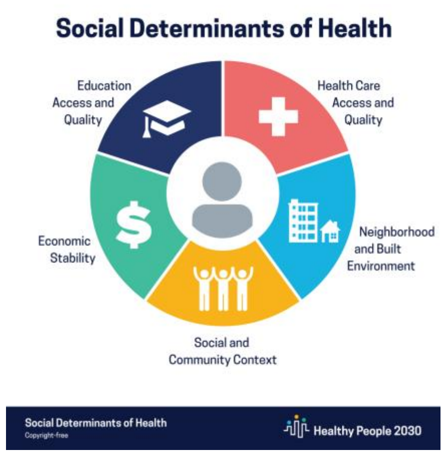

Figure 2-1 Social Determinants of Health

2.2. Domains and Indicators

Citizens' access to services and experiences that enhance health is influenced by neighborhood factors. Neighborhoods are multi-faceted, influencing people's health in a variety of ways. Drawing on related work on neighborhoods and the human health and well-being [6], we grouped neighborhood features into five domains, through which neighborhood environment influences human health: Social and Economic, Education, Natural Environment, Neighborhood, and Transportation. Each domain has indicators that capture specific neighborhood conditions. Table 2-1 below contains a list of all indicators as well as brief definitions for each.

INDICATOR	DESCRIPTION (SOURCE)
SOCIAL & ECONOMIC	
Unemployment Rate	Percentage of people aged 25-64 who are unemployed, reversed (ACS)
Poverty Rate	Percentage of population living below the Federal Poverty Level, reversed (ACS)
Low English Proficiency	Percentage of the population speaking a language other than English who speak English less than “very well”, reversed (ACS)
Health Insurance Coverage	Percent individuals age 18-64 with health insurance coverage (ACS)
EDUCATION	
Advanced Attainment	Percentage of people over 25 years old with a bachelor's education or higher (ACS)
Preschool Enrollment	Percent 3- and 4-year-old enrolled in nursery school, preschool, or kindergarten (ACS)
NATURAL ENVIRONMENT	
Pollutant Concentration (PM2.5)	Mean estimated microparticle (PM2.5) concentration, reversed (DOHMH)
Ozone	Mean estimated 8-hour average ozone concentration, reversed (DOHMH)
Summer Day Surface Temperature	Mean neighborhood-wide provisional surface temperature on typical summer days, reversed (NASA)
NEIGHBORHOOD	
Land Use Mix	Land-Use mix of commercial, residential (EPA)
Healthy Food Access	The proportion of housing units without vehicle beyond 1/2 mile from supermarket of each census tract. (USDA)
Tree Density	Tree density per acre (DPR)
TRANSPORTATION	
Sidewalk Density	The area of sidewalks divided by the sum of the area of the roadway segment and the area sidewalks in a given census tract. (DoITT)
Transit Access	Numbers of Transits(train, subway, bus, or ferry stop.) within 15 min walk distance (0.8 mile) (NYC DOT)
Network Density	Street intersection density (pedestrian-oriented intersections). Higher intersection density is correlated with more walk trips. (OSM)

Table 2-1 HCI Indicators and Domains

The selection of indicators for each domain is grounded in a cross-disciplinary literature review and is further informed by the feedback of HCI 1.0. Furthermore, we conducted detailed analyses of the predictive validity of domain and individual indicators, which influenced how the overall index was built. When building the overall score, the weight given to each indicator and domain is based on how well the indicators and domains predict long-term health outcomes.

In the following, we will briefly discuss the domains and indicators included in HCI 2.0 and the mechanisms through which they affect health outcomes. We give references to empirical studies that back up the indicators' inclusion in the index.

2.2.1. Social and Economic Domain (SE)

The first subdomain of the social and economic domain is economic status. In this subdomain, HCI 2.0 captures the unemployment rate, people who are receiving public assistance, and poverty rate.

The prevalence of poverty in the United States is an important public health issue. In 2020, approximately 37.2 million Americans (11.4% of the total population) lived in poverty [7]. Studies have shown that there is a clear and established relationship between poverty and health outcomes. Residents of impoverished neighborhoods or communities are at increased risk for mental illness [8], chronic disease [9], and lower life expectancy [10]. Some population groups living in poverty may have more adverse health outcomes than others. Furthermore, People living in poverty have limited access to health care, education, housing, and nutritional food, all of which have an impact on their health. Poor people are thus caught in a vicious circle: poverty breeds and ill-health maintains poverty [11].

People with stable jobs can meet their basic needs for food and clothing, keeping them out of poverty. Most jobs provide income as well as some benefits, such as health insurance, paid sick leave, and parental leave that can affect the health of employed individuals. In contrast, unemployment status has a negative impact on one's health. Unemployed people experience depression, anxiety, low self-esteem, demoralization, worry, and physical discomfort [12,13]. Unemployed people are more likely to develop stress-related diseases such as high blood pressure, stroke, heart attack, heart disease, and arthritis [14–16].

The health resource subdomain includes neighborhood health insurance coverage rates among the population under age 65 to capture levels of health care access. Health insurance coverage is a marker of health care access since it lowers the costs and increases the demand for health care. Expanding access to health services is an important step toward reducing health disparities. Lack of health insurance coverage may negatively affect health. Uninsured adults are less likely to receive preventative services for chronic diseases like diabetes, cancer, and heart disease [17,18]. Similarly, children without health insurance are less likely to receive adequate treatment for illnesses like asthma or crucial preventative services like dental care and vaccines [19].

The third subdomain is the language barrier. Research indicates that limited language skills and low literacy skills are associated with lower educational attainment and worse health outcomes. Individuals who do not speak English at home, immigrants, and those with lower levels of education are at a higher risk of having inadequate English language skills [20].

Having limited English proficiency in the United States can be a barrier to accessing health care services and understanding health information. For example, when compared to older people who only speak English, older people with limited English proficiency are more likely to have no regular source of health care [21].

Cultural barriers and socioeconomic hardships may create additional barriers to acquiring and comprehending health information for immigrants who struggle with language [22]. When compared to U.S Hispanic adult people who responded in English, Hispanic people who chose to respond in Spanish were more likely to report worse health status, lack health insurance, not have a personal doctor, and postpone seeing a doctor [23]. Quality of care is lowered when patients and providers do not speak the same language [24].

2.2.2. Education Domain (E)

The positive association between education and health is well established. High educational attainment improves health directly by people doing mental exercises that may keep the central nervous system in shape the same way that physical exercise keeps the body in shape. Education improves health indirectly through improved work and economic conditions, social-psychological resources, and healthy lifestyles [25].

Preparing students for higher education is one component of primary and secondary education. A high school diploma is required for most jobs—as well as for higher education opportunities. Dropping out of high school is connected to several severe health consequences, including a lack of job opportunities, low salaries, and poverty [26]. Students also learn about health promotion and disease prevention, such as the hazards of smoking, the importance of diet and exercise, the risk of sexually transmitted diseases, and the prevention of air, water, and food-borne diseases in high school [27]. Finishing more years of high school, and especially earning a high school diploma, decreases the risk of diseases [28].

Research indicates that the early childhood stage exerts larger effects on adult outcomes than middle childhood and adolescence. Early childhood is a crucial period for brain development, shaping nearly every aspect of one’s future health and wellbeing [29]. Early childhood programs are an important source of support for young children's mental and physical development [30]. Early childhood programs of high quality can boost earning potential while also encouraging and supporting educational attainment. Furthermore, children who participated in the comprehensive early childhood education program had a lower risk of heart disease, obesity, high blood pressure, raised blood sugar, and high cholesterol, by the time they were in their mid-30s [31]. These studies suggest that high-quality early childhood education programs can help to reduce risky health behaviors and delay or prevent the onset of chronic disease later in life.

Overall, higher education attainment can lead to improved health and well-being. Individuals with more education are less likely to report conditions such as heart disease, high blood pressure, diabetes, anxiety, and depression [32]. Furthermore, individuals with more education are more likely to exercise, drink less alcohol, and seek preventive health care when needed [25].

2.2.3. Natural Environment Domain (NE)

There are strong linkages between the health and environmental features of neighborhoods. Contaminated water, polluted air, and extreme heat are 3 environmental conditions that can negatively impact population health. According to the World Health Organization, in 2012, 12.6 million deaths (23% of all deaths) globally and almost 11% of U.S mortality (almost 300,000 deaths) were attributable to environmental factors [33].

We included two measures of airborne toxic exposures: airborne microparticles (PM2.5) and ozone concentration. Because humans take millions of breaths during their lifetimes, the cumulative effect of air quality can have a long-term impact on health. Chronic exposure to outdoor air pollutants raises the risk of heart disease, stroke, chronic lung disease, and respiratory infections [34–36].

Air temperature is another environmental condition that affects health [37]. In the last decade, the United States has seen many of the hottest years on record [38]. The elevated temperature was associated with increased risk for those dying from cardiovascular diseases, such as ischemic heart disease, congestive heart failure, and myocardial infarction. And elderly over 65 years of age as well as infants and young children, racial and ethnic minorities, people with lower socioeconomic status are most vulnerable to extreme heat [39–41].

2.2.4. Neighborhood and Transportation Domains (N, T)

The built environment can be considered a foundation for the health and wellness [42]. Creating a pleasant built environment can have a direct impact on people's mental health [43] and can also have an indirect impact on their physical health by encouraging them to walk [44,45].

Different reasons for walking necessitate different aspects of the built environment. Two key motivations for walking have been discovered by behavioral scientists: recreation and transportation. Walking for recreation refers to walking for exercise or leisure, whereas walking for transportation refers to walking to reach a destination [46]. Studies have shown that transportation walking is most strongly related to measures of land use diversity, intersection density, and the number of destinations within walking distance [47]. Following these criteria, U.S. Environmental Protection Agency (EPA) created National Walkability Index, however, it is less clear how the Index is associated with walking for leisure, as it does not capture built environment features more closely associated with leisure walking, such as pedestrian infrastructure and aesthetics [48].

To capture the elements of the neighborhood built environment and transportation planning that influence physical activity and mental health and organize them in a way that can be readily used by those directly influencing the design of the built environment (e.g., architects, builders, developers, and planners). we divided the built environment profile into 2 domains: Neighborhood and Transportation

The Transportation domain measures the walkability linked to increased physical activity [49–51]. The Neighborhood domain has elements that represent the number of destinations as well as the diversity of land use. Some features have been proven to be associated with health: access to healthy foods, which has been associated with improved nutritional quality diets, a lower BMI, and greater food security [52,53]; access to green space, linked to increased physical activity, reduced stress and improved mental wellbeing [54,55].

3. Data and Methods

The HCI 2.0 consists of indicators measured on different scales, such as counts, densities, percentages, or distances. To combine these indicators into an index, we standardized the raw values of each indicator using the common method of Z-score transformation. Next, we combined the individual indicators into five domains (social and economic, education, natural environment, neighborhood, and transportation). We used weights to combine the indicators into domains based on the strength of the relationship between each indicator and linked health outcomes. The domain scores were then combined into an overall score using the same weighting method.

All indicators were measured at the census tract level. Census tracts are neighborhoods defined by the Census Bureau and generally have a population of around 4,000 people. Their boundaries typically follow visible or identifiable local boundaries, such as intersections and roadways. The HCI 2.0 is available for census tracts with a population of over 1,500 in New York City.

3.1. Data

The indicators data comprising the HCI 2.0 were from numerous public sources, including the American Community Survey (ACS), the Environmental Protection Agency

(EPA), the New York City Department of Health and Mental Hygiene (NYDCP), the Department of Transportation (DOT), OpenStreetMap, and others.

3.1.1. Data used for calculating weights and validation analyses

To calculate indicator weights and validate the index, we relied on a data sources that include census tract level measures of adult health: health indicators from PLACES: Local Data for Better Health project (PLACE), data set is from the Centers for Disease Control and Prevention (CDC).

The PLACE project uses small area estimation methods to obtain 27 chronic disease data (5 unhealthy behaviors, 13 health outcomes, and 9 prevention practices) for the entire United States [56,57]. We used the following measures of prevalence of the following conditions among the population for calculating weights:

- Mental health not good for 14 or more days among adults ages 18 and older
- Physical health not good for 14 or more days among adults ages 18 and older

For validation analyses, we used measures of prevalence of the following conditions:

- Current asthma prevalence among adults aged ≥18 years
- High cholesterol among adults aged ≥18 years who have been screened in the past 5 years
- Coronary heart disease among adults aged ≥18 years
- Diagnosed diabetes among adults aged ≥18 years
- Obesity among adults aged ≥18 years

3.1.2. Missing Data and Outliers

We removed census tracts with missing data on more than 50% of indicators in any four domains or with a population of fewer than 1500 people because a small sample size can lead to bias and result in large z-scores that could have a disproportionate impact on the resulting domain and overall index scores for a given neighborhood. Furthermore, we bottom and top-coded each indicator at the 1st and 99th percentiles.

3.1.3. Standardization

Standardization ensured that all indicators were measured on a common scale. Specifically, we performed the common z-score standardization for each indicator, using the following formula:

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \qquad (1)$$

Where i denotes census tract, where j denotes indicator. z_{ij} is the z-score of indicator j for census tract i, x_{ij} is the raw value of indicator j for census tract i, μ_j is the mean value of indicator j for all census tracts, σ_j is the standard deviation of indicator j for all census tracts.

To ensure that higher values always indicate more healthy, we standardized the directionality of each indicator by multiplying the standardized score of some indicators by -1. Those indicators are labeled as "reversed" in Table 2-1. Figure 3-1 shows the indicators' correlation before reverse data direction.

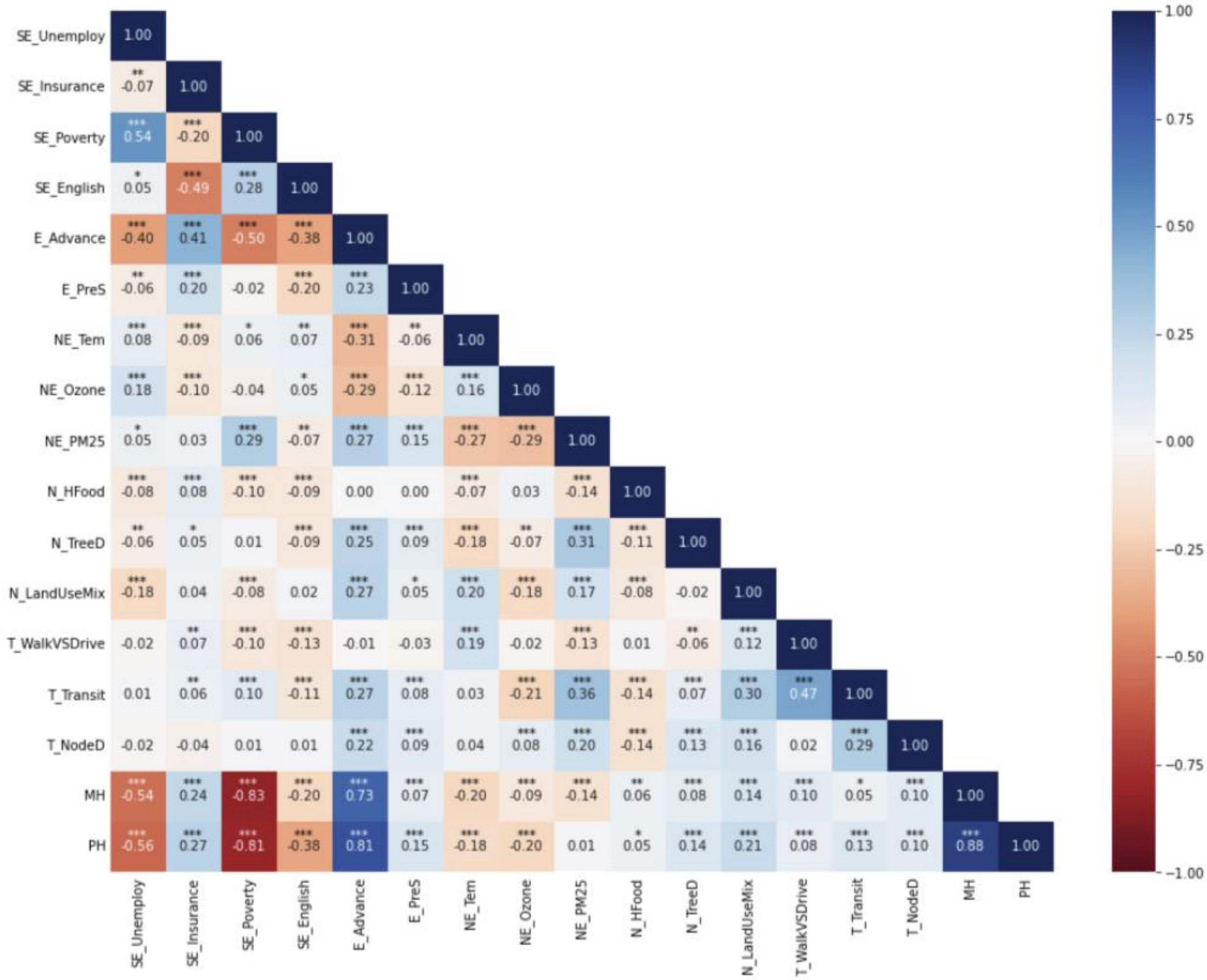

Figure 3-1 Indicator Correlation (: p-value<0.05, **: p-value<0.01, ***: p-value<0.001)*

3.2. Calculating domain scores and the overall index

For HCI 1.0, we assigned each indicator equal weight when constructing domain and overall index scores. From a predictive validity perspective, the equal weights approach implies that each variable is an equally important determinant of health outcomes. It also implies that a deficit in an influential variable, e.g., poverty rate, can be fully canceled out by an equally sized advantage in a less influential variable.

An alternative approach is to specify weights that reflect how important a given indicator is as a predictor of health outcomes. A strong empirical determinant of health outcomes receives greater weight in the overall index score. Typically, we have two ways to obtain indicators' weight. Copied them from published studies where they were reported explicitly or calculated them ourselves from regression coefficients and the mean values of dependent and independent variables [47]. However, through systematic reviews of many index tools technical reports, we found a lack of agreement on the nature of domains, domain definitions, and methods used to derive domain weights.

Our HCI 2.0 weighting combines the methods used by California Health Place Index [58] and Child Opportunity Index 2.0 [59], using the Ordinary Least Squares (OLS) regression model to obtain empirical weights. We estimated the correlation between each HCI 2.0 indicator and two health indicators from PLACE separately and then calculated the average association.

$$y_{ik} = \alpha_{jk} + \theta_{jk} x_{ij} + \varepsilon_{ijk} \qquad (2)$$

Where k denotes the health indicator's label: Mental health or Physical health, j indicates HCI 2.0 indicators, i denotes census tracts. y_{ik} is the value of k health outcome for ith census tract, x_{ij} is the value of j indicator for ith census tract, α is the intercept, ε_{ijk} is residual, we obtained θ, correlation coefficient, of each indicator from the equation (2).

Then we calculated the θ^{av} , average coefficient, of each indicator using equation (3):

$$\theta_j^{av} = \frac{\sum_k \theta_{jk}}{2} \qquad (3)$$

Next, we add up the coefficients of all the indicators in a domain and calculate the percentage of each indicator's coefficient in the domain as their weights.

$$w_j = \frac{\theta_j^{av}}{\sum_{j \in D} \theta_j^{av}} \qquad (4)$$

Where D denotes the set of indicators in a given domain.

After calculating the weights, we multiplied each standardized indicator by its respective weight and summed the weighted indicators to calculate domain scores. We then followed the same approach to calculate the overall HCI 2.0 scores, regressing the relevant outcomes on the domain scores, calculating weights, and computing the overall HCI score. Figure 3-2 shows the weight of each domain that contributed to the HCI score, as well as the weight of each indicator that contributed to each domain.

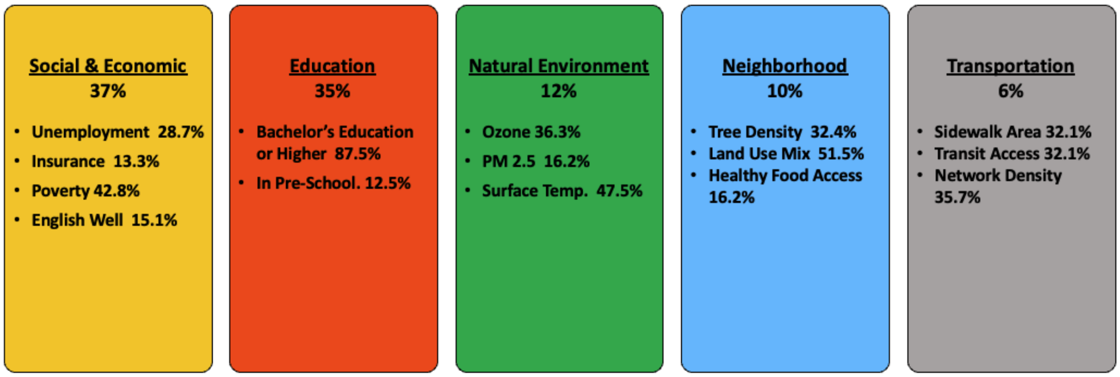

Figure 3-2 Domain Weights and Indicator Weights

3.2.1. HCI 2.0 Corridor Level Version

The HCI 2.0 scores derived from the above steps are based on the census tract scale. Since the main purpose of this project is to assist urban designers in identifying and improving vulnerable communities using street design methods, it is necessary to include corridor-level HCI scores to reflect the health of neighborhoods adjacent to the corridor.

We split the corridor by each interception and created a 0.8-mile buffer zone (15 minutes walk) on the center of each split corridor. Next, we spatially join these segments to census tracts, and if this buffer intersects only one census tract, we assign the associated HCI 2.0 score to that corridor. Otherwise, we calculate the average score of all census tracts intersecting the buffer and assign it to the associated corridor.

3.2.2. HCI 2.0 Ranking

In addition to z-scores, we also sort census tracts and corridors into 5 ordered categories labeled "very healthy", "healthy", "moderate", "unhealthy", and "very unhealthy". The thresholds were calculated based on the overall index or respective domain scores.

Specifically, census tracts and corridors with scores at or below the 20th percentile were sorted into the "very unhealthy" category. Scores above the 20th and at or below the 40th percentile were classified as "unhealthy." Scores above the 40th and at or below the 60th percentile were classified as "moderate", scores above the 60th and at or below the 80th percentile were classified as "healthy" and above the 80th percentile were classified as "very healthy".

4. Results

4.1. HCI Census Tract Version

Figure 4-1 shows the HCI census tract level heat map, red color denotes census tracts defined as “Very Unhealthy”, orange color denotes census tracts defined as “Unhealthy”, grey color denotes census tracts defined as “Moderated Healthy”, light blue color denotes census tracts defined as “Healthy”, and dark blue color denotes census tracts defined as “Very Healthy” by HCI score rating.

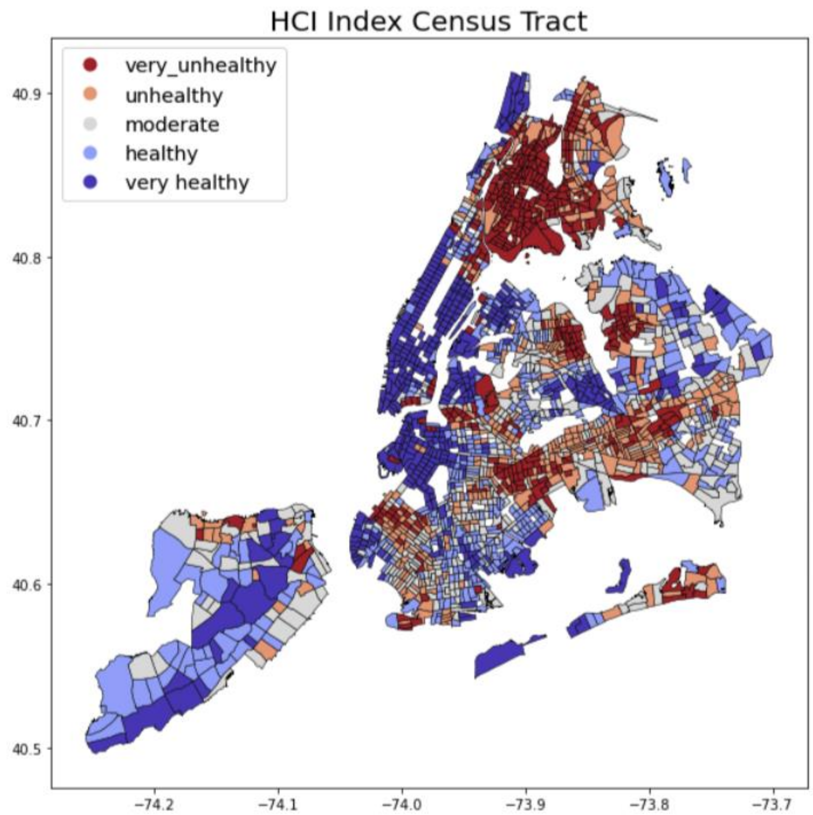

Figure 4-1 HCI Census Tract

4.2. Validation analyses

We used HCI as the independent variable to find the linear relationship with the obesity rate. As Figure 4-2 shows, the weighting method that linked with health data explained 52.4% of the variance, equal weighting method (each domain contributed 20% of the HCI, each indicator contributed equally of each domain) only explained 37% of the variance.

OLS Regression Results

Dep. Variable:	OBESITY	**R-squared:**	0.524
Model:	OLS	**Adj. R-squared:**	0.524
Method:	Least Squares	**F-statistic:**	2205.
Date:	Tue, 10 May 2022	**Prob (F-statistic):**	0.00
Time:	19:29:01	**Log-Likelihood:**	-5751.2
No. Observations:	2003	**AIC:**	1.151e+04
Df Residuals:	2001	**BIC:**	1.152e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	26.3777	0.096	276.133	0.000	26.190	26.565
HCI	-4.4859	0.096	-46.961	0.000	-4.673	-4.299

Figure 4-2 Weighted Model Result

OLS Regression Results

Dep. Variable:	OBESITY	**R-squared:**	0.370
Model:	OLS	**Adj. R-squared:**	0.370
Method:	Least Squares	**F-statistic:**	1176.
Date:	Mon, 09 May 2022	**Prob (F-statistic):**	3.97e-203
Time:	11:48:50	**Log-Likelihood:**	-6032.2
No. Observations:	2003	**AIC:**	1.207e+04
Df Residuals:	2001	**BIC:**	1.208e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	26.3777	0.110	239.980	0.000	26.162	26.593
HCI	-3.7693	0.110	-34.293	0.000	-3.985	-3.554

Figure 4-3 Equal Weighted Model Result

Figure 4-4 illustrates the relationship between each HCI class and the rates of asthma and obesity in NYC. The red dashed line represents the average disease rate in NYC. The bar plot demonstrates that the HCI effectively reflects the geographic distribution of these two diseases.

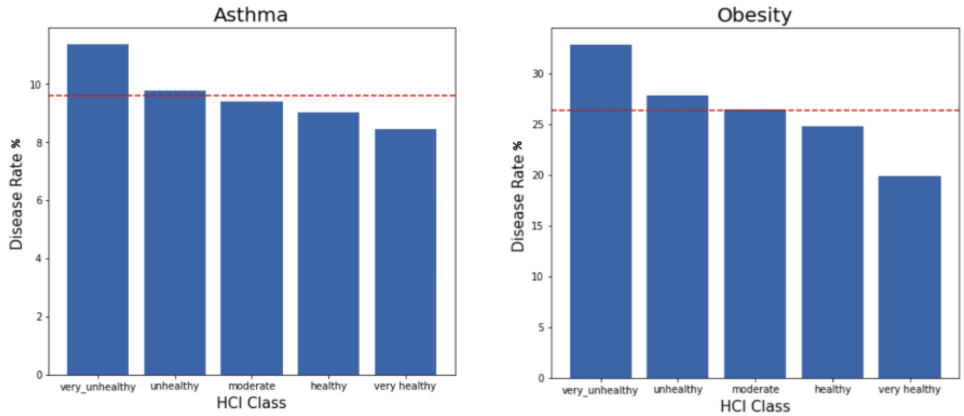

Figure 4-4 HCI Class Relationship with Asthma and Obesity

4.3. HCI Corridor Version

We remapped the HCI Census Tract Version to Corridor Version. The Corridor version took the average score of the census tract, and assigned value to the corresponding street segments. Then resorted to the HCI Classes based on the score. For the HCI Corridor version heatmap, please access HCI Corridor Map.

5. Discussion

The Healthy Corridor Index 2.0 is a composite index based on 15 indicators covering five domains: social and economic, education, natural environment, neighborhood, and transportation. While the index compares favorably to other metrics for the purposes for which it was designed, it also has certain features that previous research has identified as relevant for health or government agency care but that we were unable to include in the index due to the weighting method we used. These features may include things like vehicle collisions and fatalities, crime rates, and others. Additionally, there are trade-offs involved in combining data at the census tract level, such as calculating sidewalk area density and land use mix. Other data processing methods may also be worth considering.

The component indicators of the HCI contain a significant amount of untapped information that could potentially improve the predictive validity of the index. For example, the weights we use to combine indicators into domains and aggregate scores are constant across all tracts. However, the urban layout of the five boroughs in New York City is diverse, and indicators like transit access or network density may not be reliable metrics for determining residents' health status in certain areas. The predictive performance of the index could be improved by adopting a more flexible method for estimating weights. For example, we could allow weights to have non-linear effects and allow them to vary across neighborhoods. These limitations will be addressed in future work.

HCI 2.0 is strengthened by using data from the PLACE health data to determine the importance of each indicator in the overall index and to demonstrate its predictive validity. Based on the previous version of HCI 1.0, we expect that HCI 2.0 will more accurately represent the overall health status of neighborhoods and corresponding streets. Urban planners can use this tool to identify areas where resources should be allocated.

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Appendix: Indicators and Sources

Health Data

PLACEs Data

Description: This dataset contains model-based census tract-level estimates for the PLACES 2021 release. PLACES is the expansion of the original 500 Cities project and covers the entire United States—50 states and the District of Columbia (DC)—at county, place, census tract, and ZIP Code Tabulation Area (ZCTA) levels. It represents a first-of-its kind effort to release information uniformly on this large scale for local areas at 4 geographic levels. Estimates were provided by the Centers for Disease Control and Prevention (CDC), Division of Population Health, Epidemiology and Surveillance Branch. The dataset includes estimates for 29 measures: 4 chronic disease-related health risk behaviors, 13 health outcomes, 3 health status, and 9 on use of preventive services. Data sources used to generate these model-based estimates include Behavioral Risk Factor Surveillance System (BRFSS) 2019 or 2018 data, Census Bureau 2010 population data, and American Community Survey (ACS) 2015–2019 or 2014–2018 estimates. The 2021 release uses 2019 BRFSS data for 22 measures and 2018 BRFSS data for 7 measures (all teeth lost, dental visits, mammograms, cervical cancer screening, colorectal cancer screening, core preventive services among older adults, and sleeping less than 7 hours a night).

Geography: 2010 Census Tract

Date: December 1, 2021

Source: Centers for Disease Control and Prevention (CDC)

Social & Economic Domain

Unemployment Rate

Description: Percent of adults who are unemployed.

Definition: Reversed data direction (data x -1) to represent positive effect.

Scale: Percent

Geography: Census Tract

Date: 2019

Source: DP03, ACS 5 years estimate, 2019

Insurance Coverage

Description: Percent of adults who have insurance.

Scale: Percent

Geography: Census Tract

Date: 2019

Source: DP03, ACS 5 years estimate, 2019

Poverty Rate

Description: Percent of adults earning under the federal poverty level.

Definition: Reversed data direction (data x -1) to represent positive effect.

Scale: Percent

Geography: Census Tract

Date: 2019

Source: DP03, ACS 5 years estimate, 2019

English Proficiency

Description: Percentage of the population speaking a language other than English who speak English less than "very well".

Definition: Reversed data direction (data x -1) to represent positive effect.

Scale: Percent

Geography: Census Tract

Date: 2019

Source: S1601, ACS 5 years estimate, 2019

Education Domain

Advanced Attainment

Description: Percentage of people over 25 years old with a bachelor's education or higher.

Scale: Percent

Geography: Census Tract

Date: 2019

Source: S1501, ACS 5 years estimate, 2019

Preschool Enrollment

Description: Percent 3- and 4-year-old enrolled in nursery school, preschool, or kindergarten.

Scale: Percent

Geography: Census Tract

Date: 2019

Source: S1501, ACS 5 years estimate, 2019

Natural Environment Domain

Surface Temperature

Description: Mean census tract-wide provisional surface temperature on typical summer day.

Definition: Reversed data direction (data x -1) to represent positive effect.

Geography: 30-meter x 30-meter raster, aggregated to census tract.

Date: Aug 30, 2019

Source: NOAA Climate Data Online, USGS Landsat Level 2 Surface Temperature Science Product/Landsat Analysis Ready Data (ARD) bundle

PM 2.5

Description: Mean estimated microparticle (PM2.5) concentration

Definition: Reversed data direction (data x -1) to represent positive effect.

Geography: Census Tract

Date: 2018 (EJScreen 2021)

Source: **EJScreen 2021**, EJScreen 2021 version contains 2018 PM2.5 and Ozone data. For more information: **https://www.epa.gov/ejscreen/overview-environmental-indicators-ejscreen**

Ozone

Description: Mean estimated 8-hour average ozone concentration

Definition: Reversed data direction (data x -1) to represent positive effect.

Geography: Census Tract

Date: 2018 (EJScreen 2021)

Source: **EJScreen 2021**, EJScreen 2021 version contains 2018 PM2.5 and Ozone data. For more information: **https://www.epa.gov/ejscreen/overview-environmental-indicators-ejscreen**

Neighborhood Domain

Trees Density

Description: Trees density of the census tract

Definition: Number of trees divided by the area of the census tract

Geography: Point/Census Tract

Date: 2022

Source: **Department of Parks and Recreation (DPR)**

Land-Use Mix

Description: Land-Use mix of commercial, residential (Employment and household entropy)

Definition: Number of trees divided by the area of the census tract

Geography: Census Block/Census Tract

Date: 2021

Source: Smart Location DatabaseV3

Healthy Food Access

Description: The proportion of housing units without vehicles beyond 1/2 mile from a supermarket of each census tract.

Geography: Census Tract

Date: 2015

Source: New York State Department of Agriculture and Markets

Transportation Domain

Side Walk Area

Description: The proportion of sidewalk area

Definition: The area of sidewalks divided by the sum of the area of the roadway segment and the area sidewalks in a given census tract

Geography: LineString/Polygon/Census Tract

Date: 2021

Source: Sidewalk(DoITT), Lion 21A

Transit Access

Description: Numbers of Transits(subway, bus stops.) within 15 min walk distance (0.8 mile).

Definition: Calculate the number of Transits within 0.8 miles of the census block's centroid, then average the census block values that correspond to the census tract .

Geography: Point/Census Block/Census Tract

Date: 2022

Source: Bus Stop Shelters, Subway Entrances

Network Density

Description: 15min walking distance Intersection density in terms of pedestrian-oriented intersections.(number of intersection per acre)

Definition: Numbers of intersections within the census tract divided by the area of the census tract.

Geography: Point/Census Tract

Date: 2022

Source: OpenStreetMap via OsMnx Library