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Measuring health and human development in cities and neighborhoods in the United States

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Human development is a complex process involving interactions between individuals and their socioeconomic, biological, and physical environments. It has been studied using two frameworks: the "Capabilities Approach," implemented at the national scale, and the "Neighborhood Effects Approach," implemented at the community scale. However, no existing framework conceptualizes and measures human development across geographic scales. Here, we unite the two approaches by localizing the Human Development Index (HDI), and demonstrate a methodology for scalable implementation of this index for comparative analysis. We analyzed patterns of development in the United States, characterizing over 70,000 communities. We found that, on average, larger cities have higher HDI (higher standard of living) but exhibit greater disparities between communities, and that increases in community HDI are associated with the simultaneous reduction of a diverse set of negative neighborhood effects. Our framework produces an interdisciplinary synthesis of theory and practice for sustainable, equitable urban health and development.

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INTRODUCTION

Human development remains a major challenge in a world characterized by fast, multifaceted change but also by profound inequalities[1–3]. Better understanding the underlying processes supporting human development and how they can be accelerated in sustainable ways is a fundamental objective for both science and practice[4,5], translated into local, national and international policy objectives and commitments.

Over the last few decades two main approaches to human development have emerged at two very different scales. The first was inspired by the work of Amartya Sen[4,6] and Martha Nussbaum[5], who defined human development in terms of *capabilities*. This approach draws on a deep history of ideas about ethics and moral philosophy[6–8] as well as on recent data and evidence in many diverse situations worldwide, including a keen awareness of the local conditions of poverty, gender, ethnicity and disability in specific contexts[1,4,9]. The capabilities approach to human development inspired holistic measures of progress beyond national accounts (e.g. GDP), culminating in the definition and refinement of the well known Human Development Index (HDI)[8,10,11]. The HDI has been measured at the national level since 1990 in annual reports by the United Nations Development Programme (UNDP). The index measures the enabling factors of a long and healthy life, access to knowledge, choice and a decent standard of living[1,8]. While there have been lively debates regarding the HDI's ability to capture the full complexity of human capabilities[10], and there have been improvements in this metric's construction over time, it is now broadly used by NGOs and national governments alike to measure and compare development levels across very different contexts. Because of its widespread adoption worldwide, the HDI has arguably become the gold standard simplest metric for measuring development at the national level and, as such, it has inspired a race to the top among nations to lead rankings and improve the living conditions of their populations[1,8]. However, there is clearly a large gap between measuring the HDI at the aggregate scale of nations and the concept of human capabilities, which is tied to local environments where people grow up, live and work. Addressing this mismatch is an active research and policy goal[12] with great promise to connect the rich conceptual framework of capabilities to diverse local outcomes, including inequality, local public health, consequences of urbanization and the distributional effectiveness of social policies[10–14].

The second approach to studying human development has been more local, with a focus on place-based communities ("neighborhoods") and on the challenge of inequality and segregation, especially in cities. The study of these *neighborhood effects*, as the field became known, has been a major theme in the social sciences for over a century[15,16], but it gained special importance since the 1980s with the work of William Julius Wilson[17,18], against the background of deindustrialization in US cities, mass unemployment concentrated among working class Black communities, and the formation of inner city marginalized neighborhoods exhibiting compounding forms of social disadvantage. The literature on neighborhood effects has since grown to give an interdisciplinary account of concentrated local disadvantage that includes sociological, economic, developmental and health considerations[16,18–21]. It has also identified many different indicators of social disadvantage, with an emphasis on aspects of local human "ecological" effects[15,16,18], including concentrated crime[22–26], school performance[27], trust and collective action [16,22,24], and racial and ethnic composition and segregation[16–18]. Because of its interdisciplinary nature and diverse metrics, the study of neighborhood effects has remained far from unified conceptually, especially in terms of the identification of the web of causal processes that create and maintain cumulative local disadvantage[15,16,19,20]. As a result, policy approaches have remained somewhat narrow and arguably ineffective, including built environment interventions to mitigate disorder[25], crime prevention programs[24,25,28], rent vouchers to

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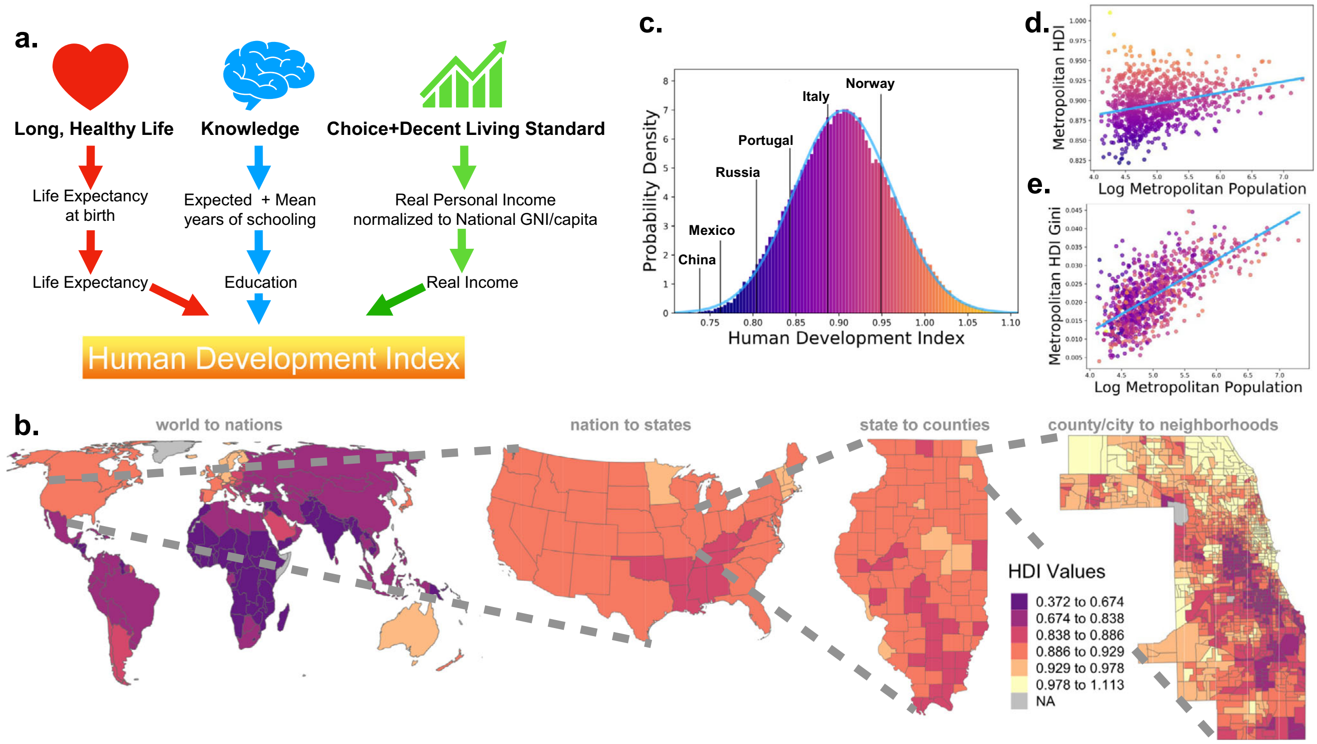


Fig. 1 Human Development Index (HDI) definition and its expression across scales. a The HDI is defined as the geometric mean of three components, indexing educational attainment, life expectancy and real incomes to given international standards. **b** The HDI (dis)aggregation across spatial scales from nations to states, counties and cities to neighborhoods (census tracts). We typically observe the greatest HDI variation at the local level of neighborhoods within larger urban areas such as Chicago. **c** The statistical distribution of neighborhood level HDI is very well described by a simple Normal distribution, $N(\mu, \sigma)$ with mean $\mu = 0.905$ and standard deviation $\sigma = 0.057$ (see Supplementary Table 1 for statistical tests). **d** Larger metropolitan areas show on average larger HDI but the effect is noisy, characterized by a linear fit on the logarithm of population size (blue line) with slope 0.011(0.005, 0.017) and intercept 0.825(0.810, 0.841), where brackets indicate 95% confidence intervals in parameter estimates. **e** The inequality in development (Gini coefficient) among local communities within metropolitan areas increases on average linearly with the logarithm of population size (blue line) with slope 0.0098(0.0092, 0.0105). The increase in development with city size and associated rise in local inequality motivates the connection between the HDI as a general indicator of human well being and analyses of neighborhood effects.

abandon troubled neighborhoods[15,20,29], non-profit social support[24,26] or cognitive treatment of youth at risk[20,28]. Recent empirical work using more extensive data sources, such as tax records, has better established the critical importance of temporal exposure to disadvantaged neighborhoods, especially during childhood, with consequences for the life course of individuals including their future income, family structure, and health[20,26,30,31]. Nevertheless, there is more agreement in this literature about data and statistical methods than about causes and solutions, with the scope of human development necessary to address systemic local disadvantage attributed to very different scales, from individuals or communities, to non-profits and public institutions.

To connect these two approaches, we must bring metrics and analyses of human development to the same local scale, reflecting the human experience on a daily basis[4,5]. Neighborhoods are critical in this sense, because they tie together outcomes to the local environments where people reside, go to school and organize socially to deal with issues of liveability, health and safety[32–34]. In this way, they represent an ideal scale to measure how local environments enable or inhibit human capabilities. Through our statistical analysis, we aim to determine how HDI at the community level relates to multiple measures of neighborhood effects. We first show how the HDI can be localized at the neighborhood scale. To this end, we create a large dataset characterizing the development of all cities and neighborhoods in the US, with over 70,000 census tracts. We then develop the methodology to consistently measure the HDI across scales, allowing the direct comparison of development in neighborhoods, cities, states and nations. We analyze the HDI values across scales in the US to show that development is typically associated with larger urban areas, but that these indeed present greater inequality between their local communities (stronger neighborhood effects). Finally, we show that high development in neighborhoods anywhere is associated with the simultaneous and systematic reduction of most forms of social disadvantage both in terms of expected values and risk.

RESULTS

We now show how development can be defined and measured consistently down to the scale of local communities, Fig. 1a. By extension, development can also be measured at any intermediate scale, including states, metropolitan areas (functionally defined cities) and counties, Fig. 1b.

Measuring human development across scales

Despite its implementation as an international standard by the UNDP since 1990, there is nothing special about measuring the HDI at the national level: All quantities involved—and their intended significance in terms of human capabilities—apply more meaningfully at the level of households or individuals. Starting from smaller scales will allows us to build up an understanding of collective effects emerging from different local human ecologies and urban network effects[35]. Analyses at local scales also give further insight into how population sorting and filtering processes occurring at different scales impact development and may lead to place-based inequalities.

It is therefore critical to preserve consistency of the HDI estimation across scales so that we can compare average levels of national development to those of specific small local communities. Figure 1a shows how the HDI is defined as a composite measure of (i) a long, healthy life, (ii) access to knowledge and (iii) economic choice and a decent standard of living. These objectives are in turn measured in the latest implementation of the HDI as an international standard via life expectancy at birth, educational attainment and real economic incomes. Although these quantities are positively correlated (Supplementary Figs. 1 and 2), there remains a large amount of variation unexplained, especially when taken at the scale of local communities (census tracts).

To measure human development as an index (i.e. a number of order 1), these three input quantities are normalized to given international goalposts to form three subindices—$I_{\rm LE}$, $I_{\rm E}$, $I_{\rm RI}$, respectively. The HDI is then given as the geometric mean of these three normalized components, $\mathrm{HDI} = (I_{\rm LE} \times I_{\rm E} \times I_{\rm RI})^{1/3}$, meaning that each of the components is considered essential for high development and that they are not mutually substitutible[10]. This makes the HDI different from many commonly used indices of vulnerability and socioeconomic status built out of principal component analyses[36] of variables such those in Fig. 3, which are weighted but additive (substitutible). Therefore, in the context of the HDI, a population that has high income but poor health (or education) will rank low. This is the main reason why the US, despite high mean income, ranks 17 in the world by HDI in 2020, behind many poorer nations.

The life expectancy index, $I_{\rm LE}$ is calculated simply as an indexed value of life expectancy at birth (LE), normalized to a maximum of 85 years and a minimum of 20 years, $I_{\rm LE} = (\mathrm{LE} - 20)/(85 - 20)$. The education index is made up of two subindices, accounting for mean years of schooling (MYS) and expected years of schooling (EYS). The mean years of schooling index applies to adults (≥25 years old) and is computed as the population average, $\mathrm{MYS} = \sum_s n(s) \times Y(s)$, where $n(s)$ is the fraction of the adult population who attained education level s, and $Y(s)$ is the number of years necessary to achieve such education level designated by the International Standard Classification of Education (ISCED)[37]. The expected years of schooling index applies to younger populations (< 25 years old), who may still be in school. It is estimated as the expected mean final educational attainment if current school enrollment rates hold, $\mathrm{EYS} = \sum_a n_r(a) \times Y_e(a)$, where a is age, $Y_e(a)$ is the expected total years of schooling for age cohort a and $n_r(a)$ is the fraction of the population enrolled in school at age a. The education index is the result of averaging these two subindices with given international goalposts, $I_{\rm E} = 1/2(\mathrm{EYS}/18 + \mathrm{MYS}/15)$. Finally, the real Income Index, $I_{\rm RI}$ is usually calculated at the national level using Gross National Income (GNI) per capita (gni), which has no simple subnational equivalent. To create a meaningful definition in small areas, we use average personal income per capita data, $I_{\rm pc}$, as $\hat{gni} = c_{GNI/I} I_{\rm pc}$, with $c_{GNI/I} = \mathrm{GNI}/I$, the ratio of national GNI to total personal income. To create real incomes, we adjust nominal incomes for cost of living at the local level. The US Bureau of Economic Analysis publishes a local purchasing power parity index (PPP) for metropolitan areas and states, which we use as $\hat{gni}_{\rm PPP} = c_{GNI/I}\, I_{\rm pc}/\mathrm{PPP}$, which now applies to each level of geographic aggregation, including states, metropolitan areas and tracts. The income index is then $I_{\rm RI} = (\log(\hat{gni}_{\rm PPP}) - \log(100))/(\log(75,000) - \log(100))$, normalized to a minimum of \$100 real dollars per person/year and to a maximum of \$75,000. This upper value is commonly surpassed in US census tracts, resulting in a values for the local income index > 1. In their latest report[9], UNDP capped gni at this upper bound for three city states so that it would not dominate the overall HDI, which we do not do here. Moreover, the use of logarithms in the income index follows UNDP construction conventions, recognizing the broad statistics (typically lognormal) of personal income in modern societies and smaller marginal benefits at high incomes[1,35].

A previous study found that the HDI's even statistical weighting of its three components accurately captured the degree of variation between the components across years at the national level[38]. To assess whether this was true at the census tract level, we performed a Principal Components Analysis of the three sub-indices. We found that the first principal component (PC1) was positively correlated with all three sub-indices, and accounted for 72.5% of the variance. The normalized weights of the Income Index, Education Index, and Life Expectancy Index were .35, 0.36, and .28 respectively, for PC1. This is close to equal weighting (which would be 0.33) of the three components, supporting the use of the HDI equation to aggregate these three quantities at the tract scale.

The consequences of these definitions are transparent and algorithmic. We provide code and data (see Materials and Methods) to allow readers to replicate our definitions and analysis, as well as generalize them to other contexts. Given appropriate data, analogous calculations can be easily developed for other nations and over time, which may improve on a few limitations of present datasets, see Materials and Methods.

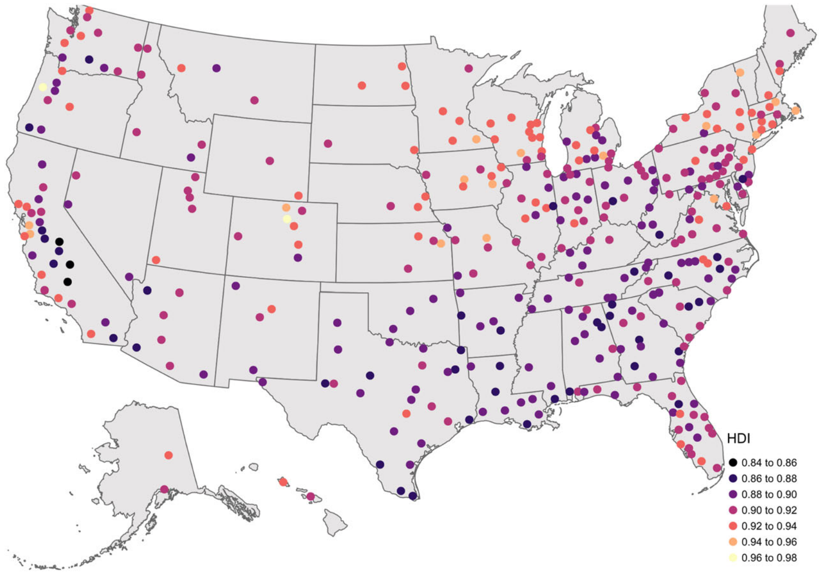
Human development in US cities and states

We now compare the HDI variation cross-sectionally across scales including states, metropolitan areas and neighborhoods. The general HDI statistics in census tracts across the entire nation is very well described by a normal distribution, Fig. 1c. We also tested a number of alternative statistical descriptions, Supplementary Table 1.

The consistent construction of the HDI across scales allows us to compare development in each local community to nations or to the temporal trajectory of US development. We see in Fig. 1c that while Norway (the top nation by HDI in 2020[9]) has a larger HDI than the US average, about 19.6% of the US population (and 18.5% of census tracts) exceed this level. Similarly, 6.5% of the US population (7.9% of tracts) lives at standards of development below Russia, 0.7% (0.9% of tracts) at standards below Mexico, and 0.2% (0.3% of tracts) at standards below China. The discrepancy between percent of population and of tracts at each level reflects the fact that very high HDI communities tend to be part of larger cities and have more populous tracts.

Despite the simplicity of the national tract-level HDI statistics in Fig. 1c, the same is not observed at smaller scales reflecting regional and local biases to lower or higher development. Figure 1d shows that there is a general statistical tendency for larger US metropolitan areas to display higher levels of development. An even clearer trend, however, is the rising inequality in development, measured by the Gini coefficient between tracts, Fig. 1e. These urban scaling effects of population size[2,35] are very general and apply also to each HDI subindex and are even larger if income is not adjusted for local purchasing power in larger, more expensive cities, Supplementary Figs. 3–7. Together these statistical trends mean that while larger cities tend to provide better environments for development overall, they also show a widening gap between their local communities, an issue discussed below under the theme of neighborhood effects.

As illustrations of higher HDI and greater inequality with city size, consider that the ten most developed US local communities, with HDI > 1.1, all are part of only three large metropolitan areas. New York City has the greatest number (six), located by New York University and Washington Square and by Central Park, followed by Washington DC (three). The single highest HDI = 1.13 community in the US was in the Boston-Cambridge-Newton metropolitan area (Coolidge Hill, by Harvard University). By contrast, the tracts with the lowest HDI nationwide are not what



State/Federal District	HDI	Metropolitan Area	HDI
Massachusetts	0.9407	Boulder, CO	0.9624
Connecticut	0.9378	Corvallis, OR	0.9622
Vermont	0.9348	Ann Arbor, MI	0.9570
New Hampshire	0.9345	Iowa City, IA	0.9567
Minnesota	0.9330	San Jose-Sunnyvale-Santa Clara, CA	0.9557
New Jersey	0.9281	Bridgeport-Stamford-Norwalk, CT	0.9553
District of Columbia	0.9273	Ames, IA	0.9532
Maryland	0.9271	Lawrence, KS	0.9496
North Dakota	0.9244	Boston-Cambridge-Newton, MA-NH	0.9491
Colorado	0.9240	San Francisco-Oakland-Hayward, CA	0.9486
Texas	0.8964	Gadsden, AL	0.8647
South Carolina	0.8935	McAllen-Edinburg-Mission, TX	0.8641
Nevada	0.8919	Lake Havasu City-Kingman, AZ	0.8637
Oklahoma	0.8879	Laredo, TX	0.8614
Tennessee	0.8874	Dalton, GA	0.8614
Kentucky	0.8843	Brownsville-Harlingen, TX	0.8605
Alabama	0.8839	Yakima, WA	0.8604
Louisiana	0.8838	Pine Bluff, AR	0.8601
West Virginia	0.8832	Bakersfield, CA	0.8595
Arkansas	0.8798	Visalia-Porterville, CA	0.8579
Mississippi	0.8762	Madera, CA	0.8572

Fig. 2 Human Development in US States and Metropolitan Areas. Mapping the HDI of different metropolitan areas (left), allows us to observe which places lead solutions that promote greater human capabilities, and which lag. The differences can be ranked, with the top and bottom States and Metropolitan Areas shown on the right. States and cities with larger public efforts in education, healthcare and innovation tend to be leaders. This pattern is clearer at the city level where "college towns" and urban areas with higher concentrations of education and research top HDI rankings, regardless of geography even in lower performing states. The top HDI micropolitan area is Los Alamos, NM.

we may think of as standard communities. Most are dominated by institutions concentrating disadvantaged populations, particularly jails, but also asylums and rehabilitation centers. For example, in New York City metro, the census tract with lowest HDI in the nation contains the Northern State Prison (and Newark airport) with HDI = 0.443. The other two are Sing Sing Correctional Facility and Rikers Island. In almost every region, the tracts with the lowest HDI are jails and other institutions that, for various reasons, disproportionately concentrate disadvantage.

These patterns of high and low development have interesting expressions when used for ranking US states and urban areas, Fig. 2. US states are significant units of analysis because many important policy decisions occur at this scale, from health care and education to land use and transportation[39]. The top US state for HDI is Massachusetts with HDI = 0.967, significantly better than any nation worldwide. By contrast, the bottom HDI state is Mississippi with a value of 0.876, similar to Poland, Fig. 2. These differences fall along urban-rural differentials in HDI, but are also likely to reflect state level policies concerning education, healthcare and other facets of human capabilities, Supplementary Figs. 8 and 9.

For metropolitan areas, Boulder, CO tops the rankings with HDI = 0.982 as the result of high performance in all HDI components, with education and income index values both >1. There is a general "college town effect" driving the highest performing cities irrespective of geography, meaning that cities that concentrate higher education and research tend to do very well. Other examples include Corvallis, OR, and Ames, IA, Silicon Valley (San Jose, CA metro) and Boston-Cambridge. Among the smaller micropolitan areas, Los Alamos, NM (home of the eponymous national laboratory) has the highest HDI of any micro- or metropolitan area in the US with HDI = 1.009.

It is interesting to note that the high HDI college town effect is not purely local as it presents spillover effects into surrounding communities. In fact, college campuses tend to score low on HDI because of a strong concentration of students with little or no income. However, the HDI of surrounding census tracts tends to be elevated, likely because colleges and research institutes create environments that attract other highly educated and entrepreneurial people. This effect is not only observable for micropolitan and small metropolitan areas with large colleges and research facilities (like Boulder and Los Alamos), but also in the local areas around such institutions in larger metropolitan areas, as noted above for Washington Square in New York City and Coolidge Hill in Boston. By contrast, the lowest ranked metropolitan areas, such as Gadsden, AL and Lake Havasu City-Kingman, AZ, tend to be (post-)industrial, agricultural or border cities, mostly in the South and Southwest. These cities perform relatively well in terms of the Income index; Gasden, AL, has an income index value of 0.97. Their relative challenges of development concentrate on deficits of life expectancy and education.

We see that HDI rankings of US urban areas and states naturally lead to a rich set of comparative analyses revealing consequences of policy, local history and culture across scales, as well as collective socioeconomic dynamics associated with scaling and agglomeration effects in urban areas and their constituent communities to which we now turn.

Human development and neighborhood effects

Studies of neighborhood effects start by recognizing and measuring (i) inequalities between different neighborhoods, especially in major North American cities[23]; (ii) that inequality is place-based, persistent and self-reinforcing[40], creating vicious cycles of cumulative (dis)advantage, and (iii) that the effects of neighborhood environments on people are "ecological" and cumulative in terms of temporal exposure, especially during childhood[18,20,22,27,31]. Moreover, the effects on individuals are complex, involving interlocked social, economic, cognitive and behavioral outcomes, including mental health[23], educational attainment[23,27], physical health[21,41,42], crime[26,41], lack of trust and other measures associated with social disadvantage[22]. Neighborhood effects are clearly identifiable through spatially resolved maps of socioeconomic outcomes in any city, which often manifest variations within short distances of about a kilometer[2].

We propose that the capabilities approach to human development provides a theoretical frame of reference for this body of knowledge and practice. To do this, we show that greater HDI observed at the scale of neighborhoods is associated

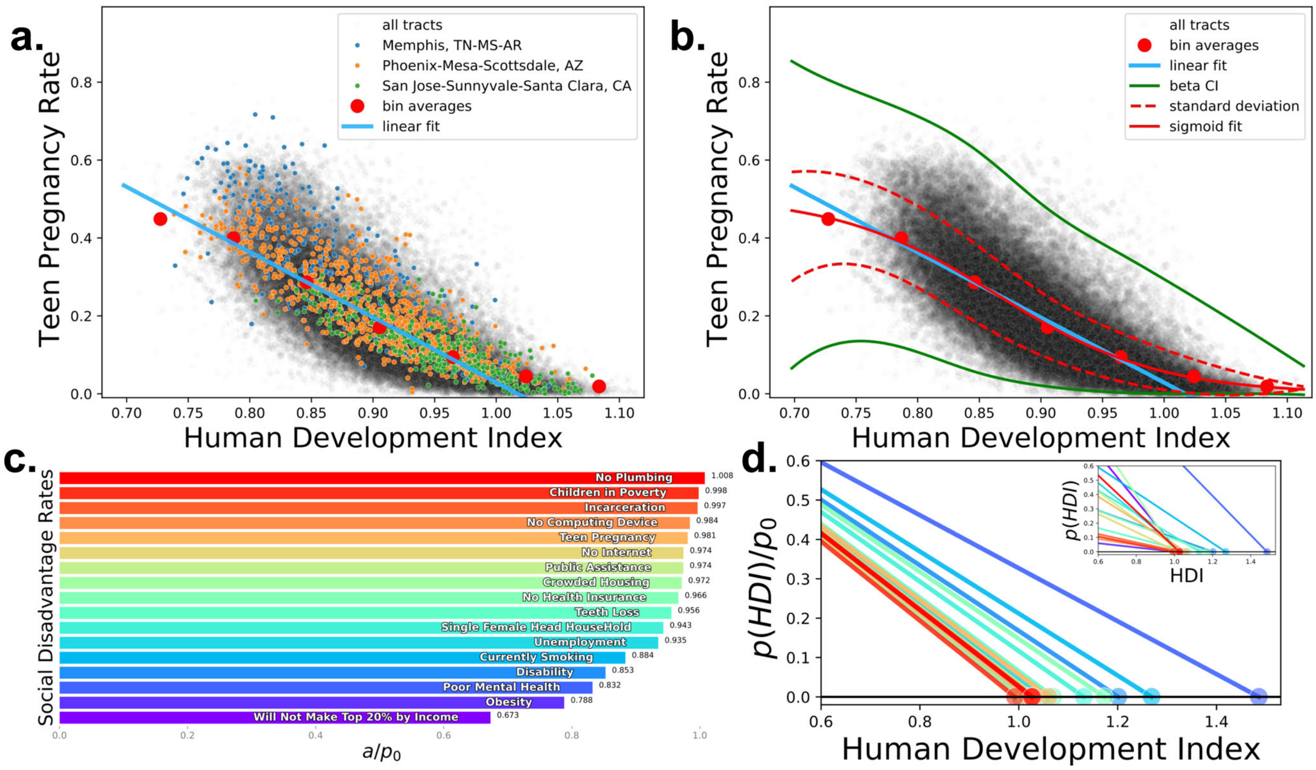


Fig. 3 Higher human development index values are associated with many different lower social disadvantage rates. a Highlights for three different metropolitan areas with low, medium and high HDI for teen pregnancy rates. The average rate (red circles) decreases approximately linearly (blue line) with HDI. **b** A Beta distribution with parameters varying with HDI gives a better description of the rate statistics, including slowing down at very high HDI and associated variance (risk) reduction. **c** The slopes of the negative linear relation between 17 rates of social disadvantage and HDI, shown in **d** inset. **d** When adjusted for rate initial magnitudes at low HDI, all social disadvantage rates display similar slopes and vanish for HDI → 1 or slightly above, see Supplementary Figs. 20 to 28 and Supplementary Tables 4 and 5.

with systematic and simultaneous improvements in a large number of diverse socioeconomic indicators, which we characterize statistically. We assembled a set of different metrics for tracts nationwide across a variety of representative neighborhood effects studies, including those by the Opportunity Atlas[30], the US Census American Community Survey and the Centers of Disease Control PLACES dataset, see Materials and Methods. Though some of these metrics relate to HDI inputs (i.e. children in poverty), most reflect outcomes expressing distinct facets of disadvantage at different life stages, as well as segregation and poverty, Fig. 3. Examples are teen pregnancy, poor mental health, or incarceration.

As an example, Fig. 3a, b illustrates the typical relationship between HDI and teenage pregnancy rates at the tract level across all places in the USA (71,513 tracts). Figure 3a highlights tracts from three different metropolitan areas—Memphis TN, Phoenix AZ, and San Francisco CA—with low, medium and high average development, respectively. The average relationship between teenage pregnancy rates and HDI shows a clear negative correlation reflecting both the decrease in the mean expected rate and its variance with larger community HDI. We characterized this behavior in three ways. First, by a simple linear regression fit (blue line) that captures most of the average variation and, second, by a statistical model of rates as a Beta distribution, with parameters dependent on the HDI (red and green lines), see Supplementary Text for motivation and explanation. In addition, we also performed a factor analysis of this set of variables.

The linear fit gives us the essence of this variation: average teenage pregnancy rates, $p(\mathrm{HDI}) = p_0 - a \times \mathrm{HDI}$ at the tract level display a negative slope of $a = 1.671$ versus HDI. This linear fit predicts that at HDI = 1.02, teenage pregnancy rates should vanish. This is not quite correct because this decrease slows down at very high HDI. The Beta distribution model, $p(\mathrm{HDI}) \sim \mathrm{Beta}(\alpha, \beta|\mathrm{HDI})$, gives a much better description of data both in terms of the HDI dependence of the mean (solid red line) and its variance (dashed lines) or 99% confidence interval (green). To estimate this distribution, we binned census tracts according to their HDI values and estimated the Beta parameters (α, β) for each bin, Supplementary Fig. 29. We then fitted the variation of these parameters with HDI to produce a continuous description of the conditional statistics (red and green lines in Fig. 3b). In most cases, the variation of the distribution average and standard deviation is well fit by a logistic curve (solid red line), which approximates a linear relationship at mid-HDI (blue line), while saturating to zero at high HDI and slowing down their increase while also increasing variation at low HDI. Supplementary Tables 2 and 3 summarize linear fits for various quantities at the metropolitan and micropolitan level, illustrated in Supplementary Figs. 10–18. Supplementary Tables 4 and 5 summarize results for the same quantities at the tract level, illustrated in Supplementary Figs. 20–28. In addition, we show (Supplementary Figs. 19 and 31 and Supplementary Text) that race, ethnicity, and foreign background do not show strong correlations with HDI across the US, mainly because low HDI communities have varied compositions of these factors[43]. However, in cities with a history of racial segregation, there is a greater association between race and HDI[17,22,26,44].

In addition to linear regressions and Beta density modeling, we have also performed a principal component analysis (PCA) of the joint 18 variables in Fig. 3 to show that HDI increases correlate to simultaneous decreases in all social disadvantage rates expressed as the first PCA component, which accounts for 54.5% of the relative variance, Supplementary Table 6.

Figure 3c shows the slope of the average variation a in each of these rates with HDI, see also Fig. 3d inset. Normalizing these rates by their values at low HDI obtains a simple general picture where all rates decrease as human development increases and vanish around or slightly above HDI = 1, Fig. 3d. This expresses a universal trend—regardless of geography or local culture—towards the systemic mitigation and even eradication of many apparently different societal challenges at high levels of development, measured by the HDI.

DISCUSSION

We have shown how human development can be measured consistently across scales from nations down to local neighborhood communities. In this way, the HDI's historical role as the major indicator of socioeconomic progress among nations and its meaning signaling expanding human capabilities can be brought to bear on challenges of local development at the neighborhood and urban scales. This approach provides a framework that integrates the concept of human capabilities and their formation through a person's life course, the challenges associated with neighborhood effects, and the design and evaluation of sustainable development policies in cities.

Consistent with this integrated picture, we have found that larger cities tend to be sources of higher development but are also associated with starker inequalities between their neighborhoods. The typical places with the highest development are not necessarily the richest, but rather those with more intensive activity in higher education and research regardless of geography, a finding we called the "college town effect". These places allow us to visualize what a future of more widespread development may look like. Conversely, a very different kind of place concentrates disadvantage, especially jails and other institutions, with public housing projects also often in this category. These extremes illustrate the environments that create and destroy human capabilities, as sources and sinks of development.

Progress in theory and practice of local human development will necessarily require measurement and analysis across time, which has been already transformative at the national level[1,8,9]. Such longitudinal analyses remain a challenge given present data collections and, especially, the manner in which they are dispersed across different organizations. The creation of a local community HDI in the US and its relation to other tract characteristics over time hinges on an enormous statistical effort to coordinate and integrate a number of different data sources, including the US Census, the Bureau of Economic Analysis, the Internal Revenue Service, the Robert Wood Johnson Foundation, the National Association of Public Health Statistics and Information Systems and the Centers for Disease Control, among others. This kind of data collection, organization and analysis, is very recent and, as far as neighborhood level life expectancy is concerned, has been produced only once (USALEEP). We hope that the present analysis along with other recent influential studies of neighborhood effects and improvements in data sciences and technology motivate such integrated data collections on an ongoing basis towards producing a reliable benchmark for promoting development across the US over time and systematically mitigating inequalities of human capabilities.

As this type of evidence becomes more available, we expect it to drive a number of breakthroughs in policy and in social theory associated with the integrated understanding of complex social processes across scales[45–47]. First, creating more complex localized indices of sustainable development at the community scale remains the main challenge underlying the United Nations Sustainable Development Goals, adopted by 193 different nations around the world[48]. Demonstrating that such localization is possible and useful at identifying context appropriate and human-centric processes of development is critical for a fast convergence to sustainability worldwide. The localization of sustainable development indices at smaller scales has a number of other critical implications, for example allowing us to gauge inequities linked to gender or race and ethnicity much more directly and minimizing adverse distributional effects in policy.

Second, and most important, the capabilities approach to human development, along with recent findings of life course effects from varying exposure to neighborhood environments during childhood and adolescence[20,31,49], has the potential to help unify emerging findings in sociology, public health, life history theory, behavioral economics, and social psychology into a common synthetic framework capable of generating practical and systemic solutions to urgent problems of community development and health in the US and around the world[46,47]. The scope of this convergence could be profound both for interdisciplinary theory and for development policy. The urgent need for equitable and sustainable health and development make it necessary to utilize advances in data sciences to find optimal solutions. National evidence on the importance of tracking human development via the HDI and promoting context appropriate public policies—in different political, economic and cultural environments—shows that this can be done.

METHODS

Data sources

Tract-level average real incomes were calculated by down-allocating the 2015 US GNI PPP (constant 2011 international dollars) reported by the UN Statistics Division using total tract incomes from the American Community Survey (ACS) for 2010–2015. These were then adjusted to create real incomes based on regional purchasing power parities reported by the US Bureau of Economic Analysis. Non-metro tracts were adjusted for real incomes using state level, non-metro PPP. Population estimates, school enrollment, and educational attainment for the population 25 years and older were taken from the ACS 5-year estimates for 2010–2015. Life expectancy data was taken from the US Small-area Life Expectancy Estimates Project (USALEEP). Tracts where life expectancy data was not reported received county-level life expectancy values from 2014. Tracts that do not have residents in every age cohort also were filled in using county-level values for education. These make up 3.05% of the cases. For the five census tracts located in counties that also had incomplete age cohorts, only Mean Years of Schooling was used to calculate the Education Index. Social disadvantage metrics in Fig. 3 were obtained from the Opportunity Atlas[30], the American Community Survey (ACS) 5-year estimates for 2015–2019 and the CDC PLACES database, see supplementary text for details. Data and python code is provided online at https://github.com/mansueto-institute/local-hdi.

Interactive map of community HDI

A detailed interactive map of HDI at the census tract level, showing statistics and comparison to international standards, is available online at https://communityhdi.org.

Best fits and Beta density estimation

Linear and sigmoid best fits were estimated using the python package *curvefit* from *scypy.optimize*. Beta parameter estimation and density selection were performed using the python package *reliability*. Principal component analysis was performed on the set of 17 social disadvantage metrics plus the HDI at the census tract level using python package *sklearn.decomposition*, see Supplementary Text for details.

Reporting summary

Further information on research design is available in the Nature Research Reporting Summary linked to this article.

DATA AVAILABILITY

The code used to aggregate and generate the data underlying this article is available at https://github.com/mansueto-institute/local-hdi. Data sources can be found in the Methods section.

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AUTHOR CONTRIBUTIONS

S.K.S. and L.M.A.B. conceived the study, S.K.S. collected and compiled data, S.K.S. and L.M.A.B. analyzed the data, S.K.S. and L.M.A.B. wrote the manuscript.

COMPETING INTERESTS

The authors declare no competing interests.

ADDITIONAL INFORMATION

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