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RESEARCH ARTICLE

Human Development and Controlled Substance Prescribing in Ohio Counties

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ABSTRACT

Background: Human development is a holistic measure of well-being. The American Human Development Index (AHDI) operationalizes the concept for the American context, using a composite measure of income, education, and health. This work presents the first county-level examination of AHDI for the state of Ohio and examines the relationship between human development and controlled substance prescribing.

Methods: Publicly available data from the census and prior publications were compiled to calculate county-level AHDI for all 88 Ohio counties. Correlations were examined between AHDI and 4 classes of controlled substances, opioids, benzodiazepines, stimulants, and sedatives, using Pearson product moment correlation coefficient.

Results: County AHDI scores ranged from 3.3 to 7.6, with mean and median values of 4.8. At the county level, human development is negatively correlated with opioid ($r = -0.46$, $r^2 = 0.22$, $P < 0.0001$) and benzodiazepine ($r = -0.43$, $r^2 = 0.18$, $P < 0.0001$) prescribing and positively associated with stimulant prescribing ($r = 0.49$, $r^2 = 0.24$, $P < 0.0001$). Neither sedative prescribing practices ($r = 0.09$, $P = 0.40$) nor median age ($r = -0.09$, $P = 0.41$) were significantly correlated with AHDI.

Conclusion: There is a strong correlation between AHDI and prescribing of several classes of controlled substances. Work remains to ascertain mechanisms and directionality of these relationships. Whether higher prescribing in areas with lower human development is an attempt to medicate health inequity or low human development is an additional manifestation of the opioid epidemic, this study underscores the necessity of pursuing equity in all policies.

Keywords: Opioids, Controlled substances, Prescribing, Human development, Human development index

INTRODUCTION

Improving the well-being of populations is the central work of public health. Human development is a capabilitarian construction of well-being, that is, one which posits one's ability to act and exist in a manner consistent with one's values as the ultimate measure of utility.[1,2] Introduced in 1990, the Human Development Index (HDI) was an attempt by the United Nations to operationalize this idea by combining health, education, and economics into a single, holistic measure of human well-being in populations.[3]

The American HDI (AHDI), an adaptation for use within the United States, employs the same dimensions, but utilizes context-appropriate measures. Specifically, AHDI measures economic well-being using median personal earnings, health using life expectancy at birth, and education using a composite measure of educational attainment and school enrollment.[4] Measure of America, a project of the Social Science Research Council, has applied the AHDI at national, state, and, in some areas, county and local levels, examining geographic, demographic, and temporal trends.

The Ohio Automated Rx Reporting System (OARRS), a prescription drug monitoring program, was established by the State of Ohio Board of Pharmacy using powers granted by Ohio Rev Code §4729.75, a 2005 law.[5,6] The Ohio Automated Rx Reporting System seeks to reduce the misuse and diversion of controlled substances by identifying potentially criminal behavior by health care providers, identifying individuals who may need help with addiction, and driving policy decisions such as prescribing guidelines.

The Ohio Automated Rx Reporting System gathers data on Drug Enforcement Agency Schedule II, III, IV, and V drugs, and publicly releases quarterly county-level data on 4 classes of drugs: (1) opioids commonly used to treat acute or chronic pain (excluding buprenorphine, which is used to treat opioid dependence), (2) benzodiazepines used in the treatment of panic and anxiety disorders, (3) stimulants used to treat attention and hyperactivity disorders, obesity, or sleep-related disorders, and (4) nonopioid sedatives used for treatment of insomnia.

As an example of how ecological studies are conducted, one of the authors (RMK) assembled a set of state-level data for students to conduct their own studies in an introductory epidemiology class. One of the stronger relationships observed was between AHDI[7] and opioid prescription,[8] which had a strong, negative correlation coefficient.[9] To explore this relationship further, the current study calculates the AHDI for all 88 counties in Ohio, and examines the correlation between human development and physician prescribing practices at the county level. The AHDI and constituent index scores for each Ohio county are also presented for use in future research.

METHODS

Setting and Design

We used county-level data for all 88 Ohio counties. The data were collected during or around 2016. An ecological study was performed using publicly available data.

Procedures

Publicly available data were gathered from multiple sources to calculate the AHDI for each of Ohio's 88 counties. Ohio Northern University's Institutional Review Board reviewed and determined the project to be exempt from review due to the use of aggregate data.

Measures

Dependent Variables

Prescribing Practices. County-level data on controlled substance prescribing practices were downloaded from OARRS through the quarterly county data.[10] Total number of doses prescribed per capita in 2016 were compiled for opioids, benzodiazepines, stimulants, and sedatives.

Independent Variables

American HDI. The AHDI is calculated as the mean of the Income, Health, and Education Indices, constructed in accordance with published methodologies for the report Measuring America: Ten Years and Counting.[11]

Income Index. Median personal earnings were evaluated using 5-year estimates from the 2016 American Community Survey drawn from table S2001, Earnings in the Past 12 Months (In 2016 Inflation-adjusted Dollars).[12] To calculate the Income Index, the log of the median earnings (HC01_EST_VC02) was rescaled so that values of log ($16009) -log ($67730) remapped to a 0 to 10 scale.

Health Index. Life expectancy at birth in 2014, the most recent year for which data were available, was accessed via the Global Health Data Exchange to calculate the Health Index.[13,14] Life expectancy was linearly rescaled so that life expectancies from 66 to 90 years remapped to a 0 to 10 scale.

Education Index. Educational attainment drew data from 9-year estimates from the 2016 American Community Survey drawn from table DP02, Selected Social Characteristics in the United States.[15] An Educational Attainment Score was determined by summing the percentage of residents aged 25 years and older with at least a high school degree (HC03_VC95), at least a bachelor's degree (HC03_VC96), and a professional degree (HC03_VC92) and dividing the result by 100. An Educational Attainment Index was calculated by linearly rescaling scores so that Educational Attainment Scores of 0.5 to 2.0 remapped to a 0 to 10 scale.

Educational enrollment data were 5-year estimates from the 2016 American Community Survey drawn from table S1401, School Enrollment.[16] The net gross enrollment ratio was calculated by dividing the population aged 3 years and over enrolled in school (HC01_EST_VC01) by the population aged 3 to 24 years (sum of HC01_EST_VC16, HC01_EST_VC18, HC01_EST_VC21, HC01_EST_VC24, and HC01_EST_VC39). For the Enrollment index, the enrollment ratio was linearly rescaled so that values of 60% to 95% remapped to a 0 to 10 scale.

The Education Index was calculated as a weighted average of the Educational Attainment and Enrollment Indices, with Educational Attainment receiving twice the weight of Enrollment.

Age. County-level data on median age (HD01_VD02), a potential confounder, was evaluated using 5-year estimates from the 2016 American Community Survey drawn from table B01002, Median Age by Sex.[17]

Statistical Analysis

Tests for association between paired samples were obtained using Pearson product moment correlation coefficients in R (64-bit, version 3.4.3 for Windows) using the cor.test function.[18,19] Full R code for the analyses is included in the Supplemental Material. Maps showing the geographic distributions of key variables were constructed using the free and open-source geographic information system QGIS (version 2.18.3 for Windows).[20] A shapefile containing county boundaries was obtained from the Ohio Department of Transportation's Transportation Information Mapping System (TIMS).[21] Detailed methodology for constructing choropleth maps are found in Supplemental Material Appendix B. Figure designs were implemented using the Solarized color palette.[22]

RESULTS

The AHDI scores for Ohio counties ranged from a minimum of 3.3 to a maximum of 7.6, with a median and mean value of 4.8. Full study data are presented in tabular form in the Supplemental Material. The minimum score of 3.3 was observed in Holmes County, where a low Income Index and state-minimum Education Index offset a top 10 ranking on the Health Index. Delaware County had not only the highest AHDI score of 7.6, but also the first- or second-highest score in each of the subindices. A map showing the geographic distribution of human development scores is presented in **Figure 1**.

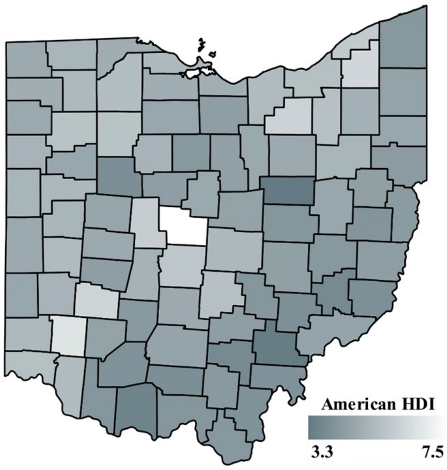

Figure 1. Geographic Distribution of the American HDI in Ohio Counties, 2016

The geographic distribution of prescribing practices for controlled substances, as reported in OARRS, are illustrated in **Figure 2**. Opioids (r = -0.46, P <0.0001), benzodiazepines (r = -0.43, P <0.0001), and stimulants (r = 0.49, P <0.0001) were all significantly associated with AHDI score at the county level (**Figure 3**). Prescribing practices for sedatives were not significantly associated with human development at the county level (r = 0.09, P = 0.40). Median age was also not significantly associated with human development in the sample (r = -0.09, P = 0.41).

DISCUSSION

In the current study, the AHDI was significantly correlated with 3 of the 4 classes of controlled substances: opioids, benzodiazepines, and stimulants. Interestingly, human development was negatively correlated with the former 2 classes of drugs, meaning better-off populations are less likely to have high rates of opioid and benzodiazepine prescribing, but positively correlated with stimulant prescriptions.

The ecological design of the current study necessitates caution when interpreting results, especially with regard to the ecological

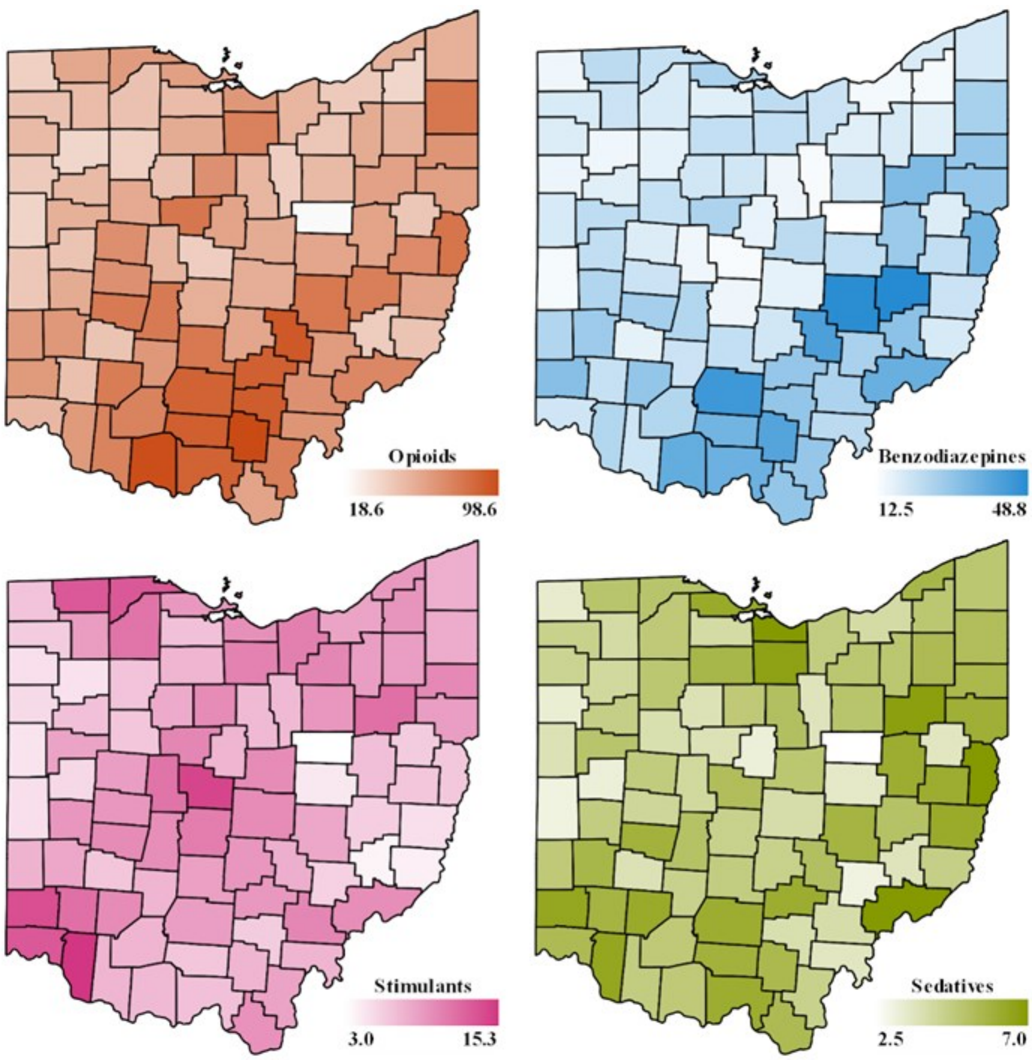

Figure 2. Geographic Distribution of Prescribing Practices in Ohio Counties, 2016. Annual Per Capita Prescribed Doses for 4 Classes of Controlled Substances as Reported in the Ohio Automated Rx Reporting System (OARRS)

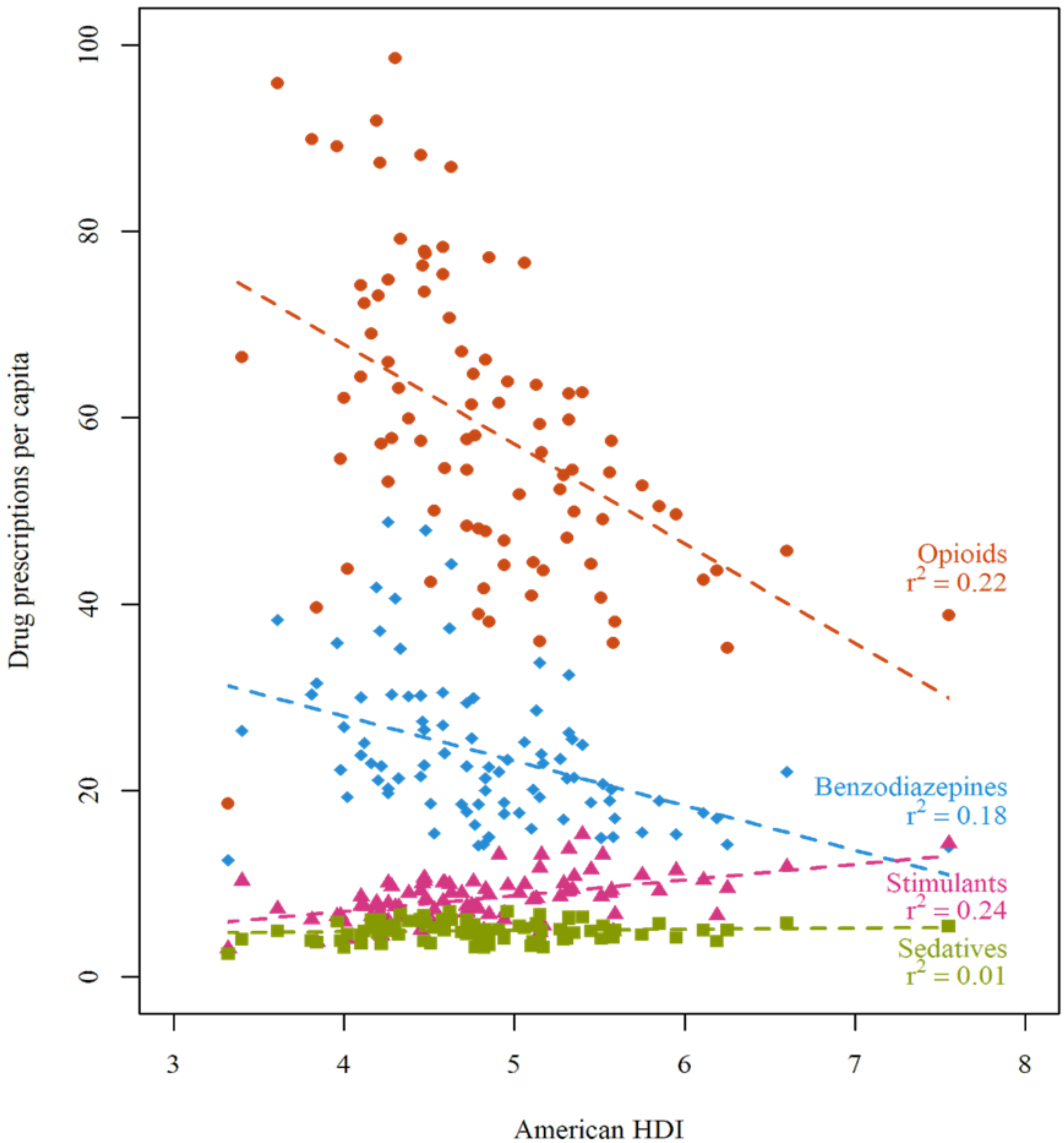

Figure 3. Scatterplot of Per Capita Prescriptions of 4 Classes of Controlled Substances Versus American HDI in 88 Ohio Counties in 2016

fallacy.[23] An association at the group level does not necessarily imply that such a relationship holds at the individual level. Further, individual-level studies would be needed to determine if one or more of the components comprising the American HDI are individually linked to prescribing practices.

Confounding is another key consideration in determining validity. Age is a frequent source of confounding in observational research,[24] and so received special attention in the current study. While prescribing practices are known to vary with age,[25] the degree of relationship between human development and age distribution is less clear. A population's age distribution might potentially impact multiple components of HDI. For example, educational attainment can only be achieved over time and earnings typically increase with age. However, age distribution, as measured by median age, was not significantly associated with American HDI score in this study. As confounders must be associated with both the cause and effect, age does not appear to be a confounder here.

Work remains to fully map the complex pathways through which social determinants influence health, but the central importance of such factors is well established.[26] As a composite measure of social determinants, causal relationships involving human development are likely similarly complex and bidirectional. The strength of the observed relationships and consistency across multiple classes of drugs support the utility of human development as a measure of well-being at the county level despite this ambiguity.

Several possible mechanisms could explain the observed relationships, in both causal directions. The components underlying the American HDI are all core social determinants of health, and in this way may shape outcomes like prescribing practices.[27] Education shapes occupation. Manual jobs may predominate in areas with less education, which may increase the prevalence of injuries requiring opioid prescriptions.[28] Low-income areas might have inferior housing options, with higher rates of crime and less access to stress-relieving green space, increasing the prevalence of anxiety disorders and subsequent benzodiazepine prescriptions.[29,30] While children from lower-socioeconomic status (SES) have been found to have higher diagnosed rates of attention deficit/ hyperactivity disorder (ADHD), children from high-SES households have had higher rates of treatment, potentially explaining greater stimulant prescriptions.[31]

It is also possible that the higher prescribing of opioids and benzodiazepines in low AHDI areas are, in a literal sense, an attempt by our health care system to medicate the sequelae of social inequity. Compelling recent work has demonstrated higher rates of reported physical pain among those who experience emotional trauma.[32] Prescribing differences may highlight physical manifestations of differing levels of human development.

There are also valid hypotheses with the opposite causal direction. For example, overprescribing of opioids and benzodiazepines, drugs with a strong potential for abuse, may undermine the social fabric in ways that reduce human development.

In all likelihood, there is a complex, bidirectional relationship between AHDI and prescribing practices. Elucidating the relative strength of these components could be valuable direction for future work.

A major limitation of the AHDI derives from its goal of adapting the concept of human development for a typical "American" context. Holmes County, the primary outlier in our sample, illustrates the limitations of the selected measures. Holmes County lies at the heart of one of the largest Amish settlements in the world.[33] Amish culture does not strongly value formal education, as evidenced by Holmes County's state-minimum Educational Index score. Despite the low score, Holmes County also had the lowest rate of opioid prescriptions, likely due to Amish patterns of medical utilization.[34]

Future studies should examine the contributions of the component indices as independent and concurrent predictors of health outcomes. More focused measures (eg, life expectancy at birth) may prove more useful for predicting specific outcomes than the composite AHDI measure. Full data are appended to facilitate such research.

The concept of human development is consistent with a vision of health as "complete physical, mental, and social well-being."[35] This is the first publication of county-level AHDI in Ohio. The strength of relationships observed in the current study suggest that AHDI may be useful for future researchers as a proxy for social determinants or wellness-related outcome.

PUBLIC HEALTH IMPLICATIONS

This work presents the first county-level examination of the AHDI for the state of Ohio and provides a potentially valuable measure for use by future researchers and public health professionals. Human development is predictive of prescribing practices, though the directionality of the relationship is not clear. Future work should explore potential causal pathways linking human development and prescribing practices. The opioid epidemic is a significant public health crisis. Whether higher prescribing in areas with lower human development is an attempt to medicate health inequity or low human development is an additional manifestation of the opioid epidemic, this study underscores the necessity of pursuing equity in all policies.

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