Iowa's Health Information Platform

Report provided to the Iowa Department of Public Health,

Substance Abuse Bureau

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Overview

At the request of the Iowa Department of Public Health, Substance Abuse Bureau and the Linkage to Care Advisory Board, the Public Science Collaborative (PSC) pursued five goals aligning with the CDC's Overdose Data to Action (OD2A) policy initiative. These include: promote health equity, move from data to action, improve preparedness for substance use outbreaks, monitor state-wide substance use, and support data informed decision-making. In the following pages, we describe the data analytics, prototype dashboards, data tools, and the underlying data infrastructure we created support implementation of these federal goals in Iowa.

If you have questions or would like additional information about this report, the dashboards data tools described herein, or the Public Science Collaborative, we encourage you to contact the principal investigators of this study, Dr. Cassandra Dorius at cdorius@iastate.edu, or Dr. Shawn Dorius at sdorius@iastate.edu.

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This project was supported by the Iowa Department of Public Health, Bureau of Substance Abuse (IDPH) via a subaward from the Centers for Disease Control (CDC) and Prevention of the U.S. Department of Health and Human Services (HHS) as part of a financial assistance award totaling $326,956 with 100 percent funded by CDC/HHS. The contents are those of the author(s) and do not necessarily represent the official views of, nor an endorsement by, IDPH, CDC/HHS, or the U.S. Government.

Goal 1: Promote Health Equity by Mapping the Social Determinants of Health in Iowa

Dashboard: https://publicsciencecollaborative.shinyapps.io/iowa_sdoh/

Data: *U.S. Census Bureau American Community 5-year Estimates (ACS), 2015-2019*

Data tool: Social Determinants of Health Index

The Iowa Department of Public Health, Substance Abuse Bureau is actively working to strengthen capacity to address health inequities in Iowa. **Health equity** is defined as the attainment of the highest possible level of health for all people by achieving the environmental, social, economic, and other conditions in which all people have the opportunity to attain their highest possible level of health. This dashboard promotes health equity by documenting the environments that create and ameliorate the multifactorial risks of substance misuse among priority populations.

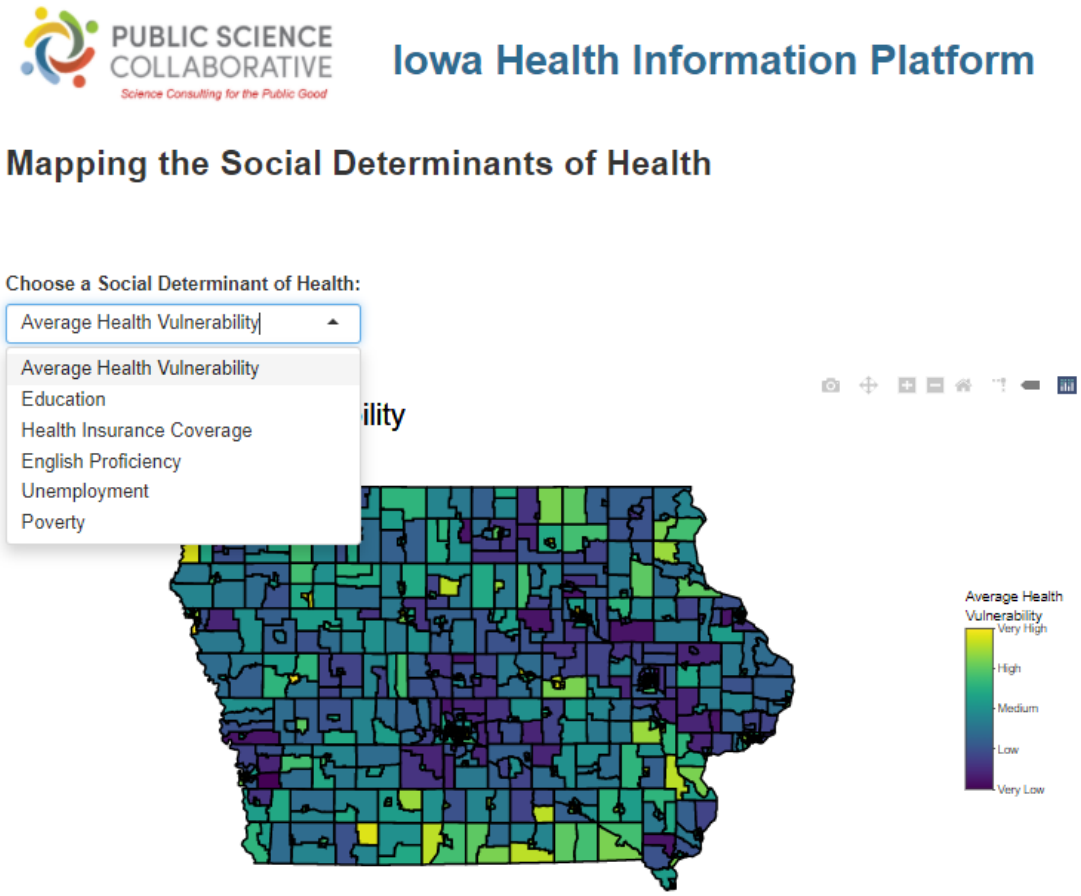
Per the recommendations from the Linkage to Care Advisory Group, we modeled our data tool on the Washington State Social Determinants of Health Website: www.doh.wa.gov/DataandStatisticalReports/HealthDataVisualization/SocialDeterminantsofHealthDashboards/CensusTractSocialDeterminantsofHealth. Also in response to advisory group feedback, the social determinants dashboard and other dashboards described in this report allow users to download data visualizations in file formats that enable reuse in prevention, treatment, and recovery initiatives, such as writing proposals, giving presentations, facilitating workshops, and identifying places in need of targeted interventions. A static example of the dynamic dashboard is presented as Figure 1.

Table 1. *Substance Use Risk Index using U.S. Census Bureau American Community 5-year Estimates (2015-2019)*

	Census Table	Description
Educational Attainment	S1501	Data table includes educational attainment level for population 25+, by sex.
Health Insurance Coverage	S2701_C05_001	Variable is percent of civilian noninstitutionalized population that is uninsured.
English Proficiency	S1601_C06_001	Variable is percent of population 5+ that speaks English less than very well.
Unemployment, 16+	S2301_C04_001	Variable is percent of population 16+ that is in the labor force, but is unemployed.
Poverty Status	S1701_C01	Data table includes poverty status by age bracket and for different income levels.

Note: Data was collected using the Census API and R tidycensus package.

Figure 1. *Mapping the Social Determinants of Health*



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Goal 2: Move from Data to Action by Creating a Substance Use Risk Index to Monitor and Support Vulnerable Populations

Dashboard: https://publicsciencecollaborative.shinyapps.io/ia_substance_use_vulnerability/

Data: *Treatment Episode Data Set- Admission and Discharge (TEDS), 2000-2018*
National Survey on Drug Use and Health data (NSDUH), 2015-2019
U.S. Census Bureau American Community 5-year Estimates (ACS), 2015-2019

Data Tool: Substance Use Vulnerability Index

The Public Science Collaborative has developed data resources to support data users and public health leaders to more effectively target substance use prevention and treatment interventions for the people in greatest need of support. Geographic 'hot spots' of people at risk for substance use disorder were first **predicted based on models of administrative data** from Treatment Episode Data on admissions (TEDS) and the National Survey of Drug Use and Health (NSDUH) data (see Tables 2 and 3) that assessed significant relationships between key substances and socio-demographic characteristics known to effect health equity and substance use vulnerability. Then, the significant predictions of risk for each substance were **overlaid with Census Bureau estimates** of these population characteristics to provide a visual representation of places with especially high concentrations of people with at-risk characteristics (see Table 4). The dashboard illustrates these results in a series of **maps of Iowa communities that are most vulnerable to substance use disorder, as well as the locations of greatest vulnerability for each of seven other commonly use substances** among people seeking treatment in Iowa, including heroin, opioids, benzodiazepine, alcohol, methamphetamine, cocaine, and cannabis. Users can access pull-down menus on this data tool to explore any one of the several underlying risk factors.

The goal of the prediction and alignment process is to reduce or prevent substance use disorder and SUD outbreaks in Iowa communities. Toward that end, we developed these data tools to enable users to visually identify areas of concern and align services and resources to best meet the needs of Iowa communities. Our *Substance Use Risk Index to Monitor Vulnerable Populations* can also strengthen the Bureau of Substance Abuse's monitoring of at-risk populations and facilitate data-informed coordination of the delivery of prevention, treatment, and recovery resources and interventions in high risk communities. Knowing *where* high-vulnerability populations live at the neighborhood level allows for a very granular application of prevention messaging, mobile clinical and treatment services, and community recovery resource investments, among other outreach efforts.

A static example of the dynamic dashboard is presented as Figure 2.

Table 2. *Substance Use Risk Index using TEDS Admission Data*

	Alcohol	Cannabis	Meth	Cocaine	Other Opiates	Heroin	Benzos
Age	Older, >35	Young, <35, <25	Middle age	>45	<25	Spikes at both ends	<25
Sex	Male	Male	Female			Male	Female
Race	Black, Hispanic	Black	White	Non-white	Asian, white	Non-white	White
Education		No college	No college	Some college	Some college	Some college	Some college
Poverty	Public Assistance	Public Assistance		Retired/Disabled	Wages/Salary, Retired/Disabled	Wages/Salary, Retired/Disabled	
Employment	Employed	Part time	Unemployed	Employed	Unemployed		Part time
Marital Status			Separated, Divorced, Widowed	Single	Married	Single	
Pop Density	Rural, Micro	Rural, Micro	Micro	Metro	Metro	Metro	Metro, Micro

Note: Empty cell indicates that no categories showed significantly increased risk.

Table 3. *Substance Use Risk Index using NSDUH Data*

	Alcohol	Cannabis	Meth	Cocaine	Other Opiates	Heroin	Benzos
Age	26-34	Young, <35, <25	Middle age	18-34	<50	26-49	18-34
Sex	Male	Male	Male	Male	Male	Male	Male
Race	White	White, Native American	White, Native American	White, Native American	White, Native American	White	White
Education	College	Some college, maybe	No college		No college	No college	
Income	>75,000	<20,000	<40,000	<20,000	<40,000	<20,000	
Employment	Employed	Unemployed	Unemployed	Unemployed	Unemployed	Unemployed	Unemployed
Marital Status	Single, separated	Single	Separated, Divorced	Single	Single	Single	Single
Pop Density	Metro	Metro	Non-metro	Metro	Metro	Metro	Metro

Note: Empty cell indicates that no categories showed significantly increased risk.

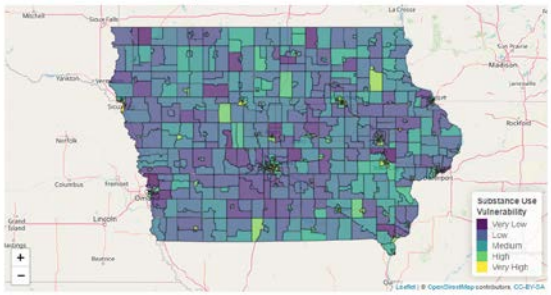
Table 4. *Substance Use Risk Index using U.S. Census Bureau American Community 5-year Estimates (2015-19)*

	Census Table	Description
Age	B06001	Data table includes population by age categories.
Sex	B01001	Data table includes population by sex.
Race	B03002	Data table includes primary race, by ethnicity.
Education	B15002	Data table includes educational attainment level for population 25+, by sex.
Poverty Status	S1701_C01	Data table includes poverty status by age bracket and for different income levels.
Employment	B23006	Data table includes employment status, by educational attainment level.
Marital Status	B12001	Data table includes marital status by sex.
Parental Status	B09002	Data table includes parental and childcare status.

Note: Data was collected using the Census API a and R tidycensus package.

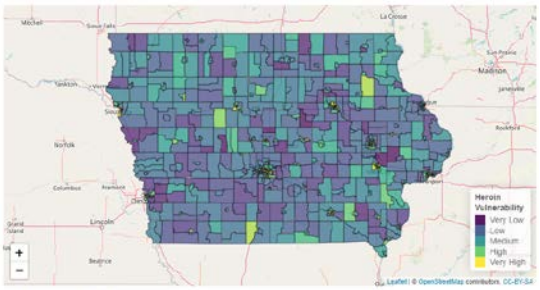
Figure 2. *A Substance Use Risk Index to Monitor Vulnerable Populations*

Substance Use Vulnerability Index



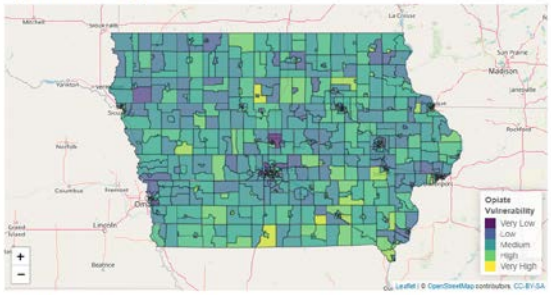
About this visualization: This index is made up as an average of all of the below, single-substance indices. It shows overall substance use vulnerability for Iowa communities.

Heroin Vulnerability Index



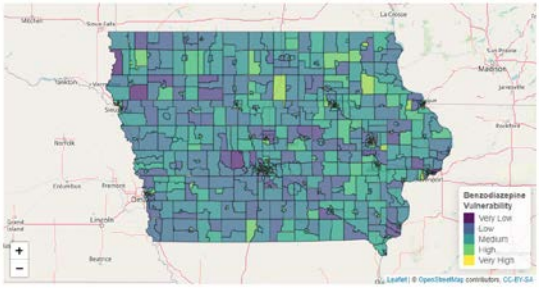
About this visualization: Components for this index are percent of population that is male; percent of population that is nonwhite; percent of population with household income below 125% of the federal poverty line; and percent of population that has never been married.

Opioid Vulnerability Index



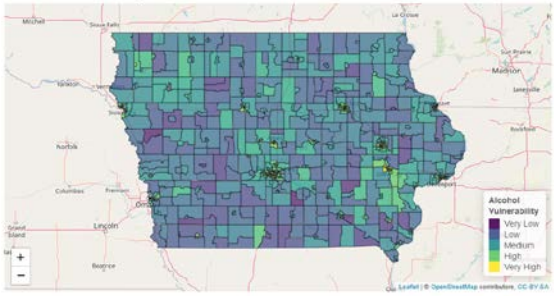
About this visualization: Components for this index are percent of population between 18 and 24 years of age; unemployment rate; and percent of population that is white.

Benzodiazepine Vulnerability Index



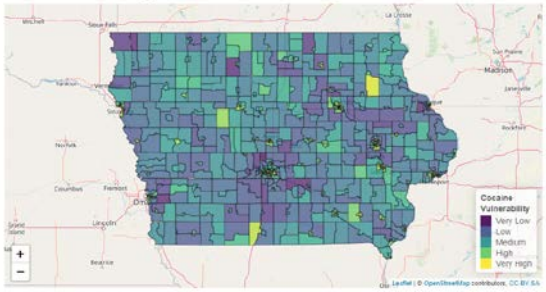
About this visualization: Components for this index are percent of population between 18 and 34 years of age; percent of population that is white; and percent of population that has never been married.

Alcohol Vulnerability Index



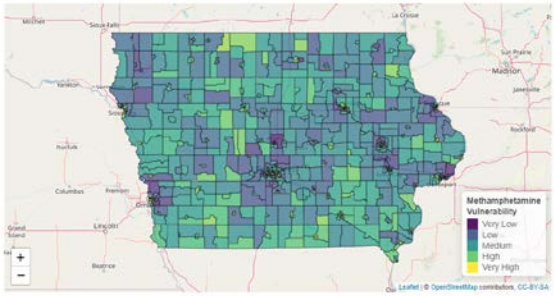
About this visualization: Components for this index are percent of population between 25 and 34 years of age; percent of population that is male; percent of population that is black or Hispanic; percent of population with a bachelor's degree; and percent of population that has never been married.

Cocaine Vulnerability Index



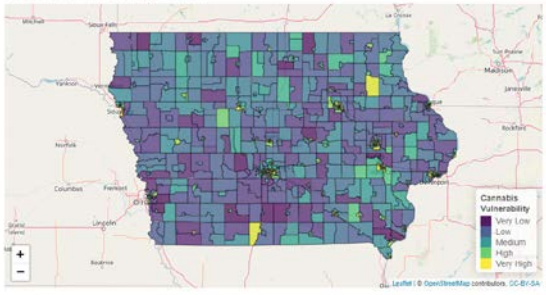
About this visualization: Components for this index are percent of population between 18 and 34 years of age; percent of population above 45 years of age; percent of population that is nonwhite; percent of population with household income below 125% of the federal poverty line; and percent of population that has never been married.

Methamphetamine Vulnerability Index



About this visualization: Components for this index are percent of population between 25 and 44 years of age; percent of population with household income below 125% of the federal poverty line; percent of population that is divorced, separated, or widowed; percent of population above 25 without a bachelor's degree; unemployment rate; percent of population that is white.

Cannabis Vulnerability Index



About this visualization: Components for this index are percent of population between 18 and 34 years of age; percent of population that is black; percent of population with household income below 125% of the federal poverty line; and percent of population that has never been married.

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Goal 3 (A): Improve Preparedness for Substance Use Outbreaks

Dashboard: https://publicsciencecollaborative.shinyapps.io/iowa_pmp/

Data: *U.S. Drug Enforcement Administration Automation of Reports and Consolidated Order System (ARCOS), 2006-2014*
U.S. Census Bureau Population Estimates, 2006-2014

Data Tool: Rural versus Urban Opioid Prescription Changes Over Time

One of the key goals of the OD2A policy initiative is to improve Iowa's preparedness for public health emergencies such as substance use outbreaks. Using data about the distribution of prescription opioids, we created interactive plots and maps that identify the location of Iowa retail pharmacies, including volumes of opioids by total sales and adjusted for the size of the local population. The population-adjusted measures allow users to assess, for example, whether pharmacies are overly concentrated in urban places or if sale rates are concerningly high in small towns and rural places. To make these sorts of analyses possible, we layered a standardized measure of prescription drug sales, Morphine Milligram Equivalents (MME), over pharmacy locations to enable direct visual detection of pharmacies distributing high volumes of prescriptions associated with overdose mortality. These assessments are key to many Public Health Departments' substance use outbreak assessments.

Prescription volume by total volume, per person volume (to account for some places having many people and other places have few people), and also changes in sales volume, are displayed in these dashboards to help the Bureau of Substance Abuse identify risk factors associated with opioid overdoses and death. We encourage you to engage with this data tool and select years in the drop-down menus to identify how the prescription volume of MME has changed over time and to visually identify which counties have the highest per person rates from 2006-2014. Further, users of these data tools can identify places where sales volume is high and rising, and even drill down to specific pharmacies driving these trends. The dashboard allows users to monitor changes in the distribution of opioid prescriptions.

The plot at the bottom of the website projects a statistical model that shows counties who initially had relatively low prescription opioid rates in the 2006 and have been "catching up" with the high volume counties over eight ensuing years. IHIP users can interact with this data tool to identify specific counties where opioid prescription rates are higher or lower than what is expected, based on their size population size.

A static example of the dynamic dashboard is presented as Figure 3. And a static example of the dynamic data tool is presented as Figure 4.

Figure 3. *Improving Outbreak Detection with Prescription Drug Monitoring*

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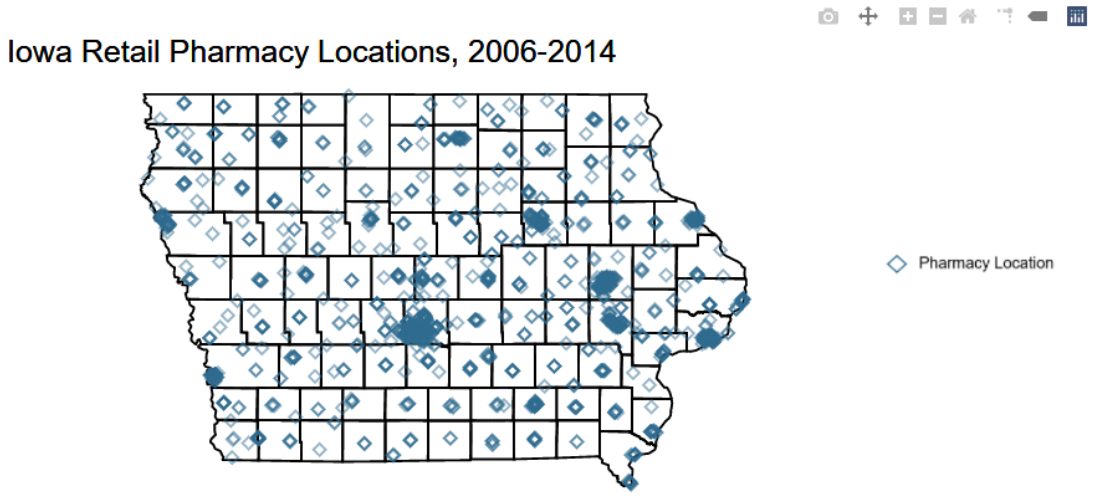
Prescription Monitoring Program (PMP)

How to use these visualizations: All plots and maps are interactive, with tooltips that appear when the user hovers over a point. Plot images can also be downloaded use the camera icon in the upper right hand corner of each plot. The other buttons allow the user to pan around the plot, zoom in, zoom out, and return to the original zoom.



About this visualization: This map shows locations of retail pharmacies in Iowa that appear in the ARCOS dataset from 2006-2014. Pharmacies are concentrated around population centers like Des Moines, Cedar Rapids, Davenport, and Iowa City.

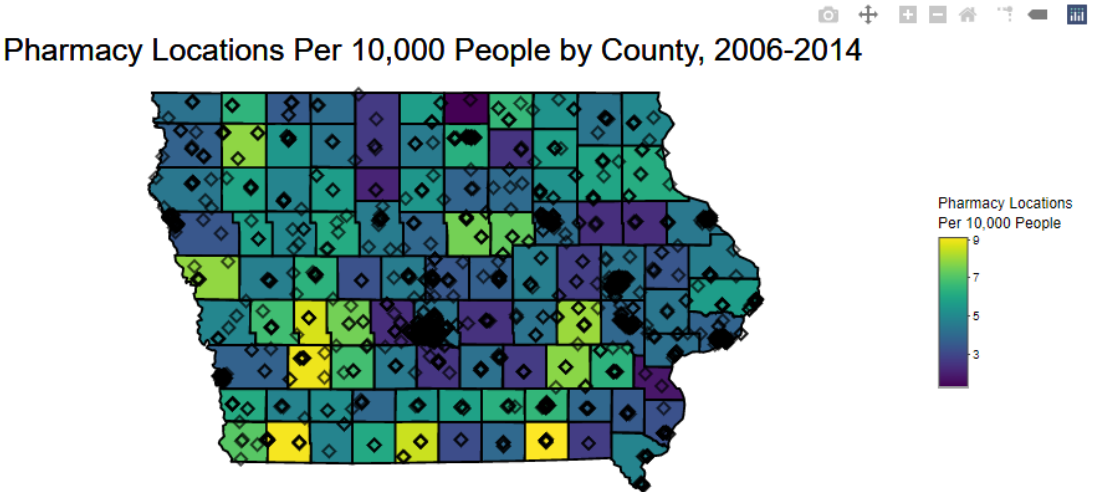


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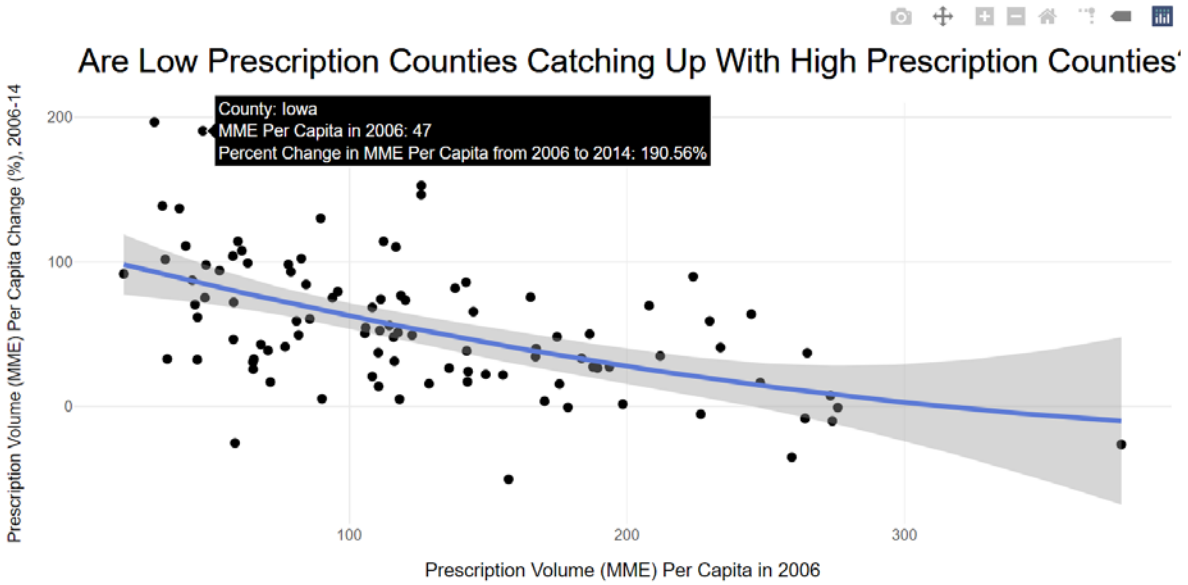
Figure 4. *Model of Changes in Low Prescription Counties Relative to High Prescription Counties, Per Capita Change from 2006-2014*



About this visualization: In this plot we can see whether there is a relaitonship between prescription volume per capita in 2006 and the change in prescription volume per capita from 2006 to 2014. The plot indicates that there is a moderately strong relationship, where counties with a smaller prescription volume per capita in 2006 "caught up" on average and have a larger increase in prescription volume per capita from 2006 to 2014 than counties with a larger prescription volume per capita in 2014

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Goal 3 (B): Improve Preparedness for Substance Use Outbreaks

Dashboard: https://publicsciencecollaborative.shinyapps.io/IDPH_STI_rates/

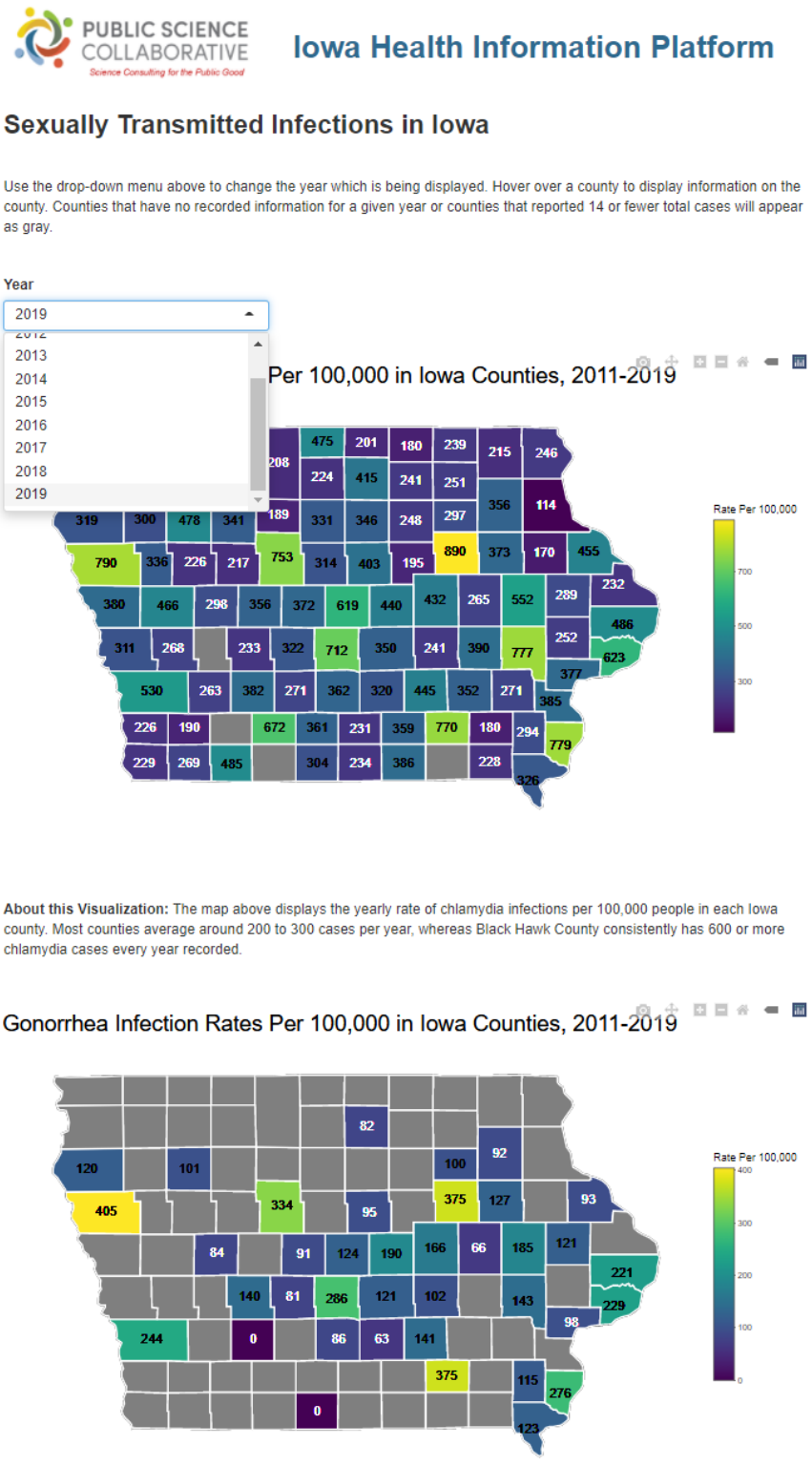
Data: *The Iowa Public Health Tracking Portal, Sexually Transmitted Disease data (IDPH STD), 2011-2019*
U.S. Census Bureau American Community 5-year Estimates (ACS), 2015-2019

A crucial goal of the OD2A funding is to improve the state's preparedness for public health emergencies such as substance use outbreaks. Collecting and evaluating information on sexually transmitted infections (STI) has been identified by public health as an effective way to monitor and predict substance use outbreaks. Using data from the Department of Public Health's Tracking Portal, we mapped county-specific chlamydia and gonorrhea infection rates per 100,000 people from 2011-2019, as well as changes in infection rates. Using these tools, stakeholders who engage the IHIP system will be able to track STI outbreaks, which are positively correlated with increased substance use, intravenous drug use, and risky sexual behaviors (Kidd et al., 2019; Shearer et al., 2020). Rising STI prevalence among people who use methamphetamine derives from high-risk sexual behavior within this population (Herbeck et al., 2013; Hittner, 2016). Additionally, research finds that individuals who use both methamphetamine *and* opioids have higher STI rates than people who use only opioids or methamphetamine (Shearer et al., 2020). Owing to these associations, prevention agencies and organization are advised to monitor intravenous and non-intravenous methamphetamine use to better identify, understand, and predict substance use outbreaks.

We encourage you to use the drop-down menus on these interactive data tools to see how the STI rates have changed over the last decade and to identify counties with high or rising STI rates. In its current form, the data dashboard provides location-specific STI rates for the ten largest counties in Iowa that collectively account for 53% of all residents of Iowa. Future revisions of this dashboard will include syphilis data, which has been shown to have a particularly strong association with substance use outbreaks.

A static example of the dynamic dashboard is presented as Figure 5.

Figure 5. *Improving Outbreak Detection of Sexually Transmitted Infections*



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Goal 4: Monitor State-wide Substance Use

Dashboard: https://publicsciencecollaborative.shinyapps.io/TEDS_Dashboard/

Data: *Treatment Episode Data Set- Admission and Discharge (TEDS), 2000-2018*

National Survey on Drug Use and Health data (NSDUH), 2015-2019
U.S. Census Bureau American Community 5-year Estimates (ACS), 2015-2019

A key goal of Iowa's OD2A funding is to improve preparedness for public health emergencies, such as outbreaks, by monitoring state-wide substance use. The administrative data collected when people enter federally funded substance use treatment programs in Iowa (e.g., TEDS) is considered a gold-standard for monitoring substance use trends in the state. These data have been utilized here to develop measures of harmful opioid use, as well as harmful use of the most commonly reported substances at admission to treatment in Iowa, including heroin, benzodiazepine, methamphetamine, cocaine, cannabis, alcohol, and other substances.

Our data dashboards allow people to investigate important patterns and trends in harmful substance use with simply drop-down menus. Users of these data tools can see, for example, which drugs are most and least likely to be reported as a primary, secondary, or tertiary substance of choice when people enter treatment in Iowa. Users can also 'drill down' to specific data ranges and substance combinations, as well as identify how rates of substance use vary by age and gender.

Per the recommendations from the Linkage to Care Advisory Group, this data tool was based on Arizona State's Opioid Interactive Dashboard:
https://www.azdhs.gov/prevention/womens-childrens-health/injury-prevention/opioid-prevention/opioids/index.php#dashboard.

Static examples of the dynamic dashboard are presented as Figures 6 and 7.

Figure 6. *Monitoring State-wide Substance Use with Treatment Admissions Data*

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Figure 7. *Drilling Down by Substance of Choice, Year, Age, and Gender*

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Goal 5: Support Data Informed Decision-making

Data tool: https://publicsciencecollaborative.shinyapps.io/TEDS_Opioids_Combinations/

Data: *Treatment Episode Data Set- Admission and Discharge (TEDS), 2000-2018*

An important goal of the OD2A policy initiative is to support states, such as Iowa, in the collection, cleaning, anonymizing, and presenting of complex data streams as infographics, charts, and maps to help a wide range of stakeholders make evidence-based and data-informed decisions. An example of this process can be found with our Opioid Polysubstance Use dashboard. The intentional mixing of opioids with other substances—either by consuming two or more substances at the same time or in rapid succession—is a long-standing public health concern known interchangeably as polydrug use or polysubstance use (Anglin et al., 2000).

Health experts characterize polysubstance use as a serious problem because it increases the likelihood of harmful substance use, including, overdose, dependence, withdrawal, and addiction for each drug consumed. Furthermore, combining substances can place a significant burden on the cardiovascular and respiratory systems, leading to overdose, coma, cardiac complications, or even death (Vertava Health, 2021). One reason polysubstance use jeopardizes health is that when a person mixes depressants such as opioids, heroin, benzodiazepines, or alcohol with stimulants such as methamphetamine or cocaine, their brain and central nervous system receive simultaneous, conflicting messages that elevate risk of overdose or death by suppressing the body's natural alerting systems (Vertava Health, 2021). Likewise, when people use two or more stimulants, they place an ofttimes significant additional burden on the heart and respiratory system that can manifest in acute (e.g. heart attack) or long-term cumulative negative affects health (MedlinePlus, 2021).

Local and state policy makers, health officials, and criminal justice partners in Iowa are rightfully concerned about polysubstance use. This dashboard provides an opportunity to explore the frequency of self-reported opioid use and common substances reported in co-occurring use across a variety of visualizations.

A static example of the dashboard is presented as Figure 8.

Figure 8. *Supporting Data Informed Decision-making around Polysubstance Use*

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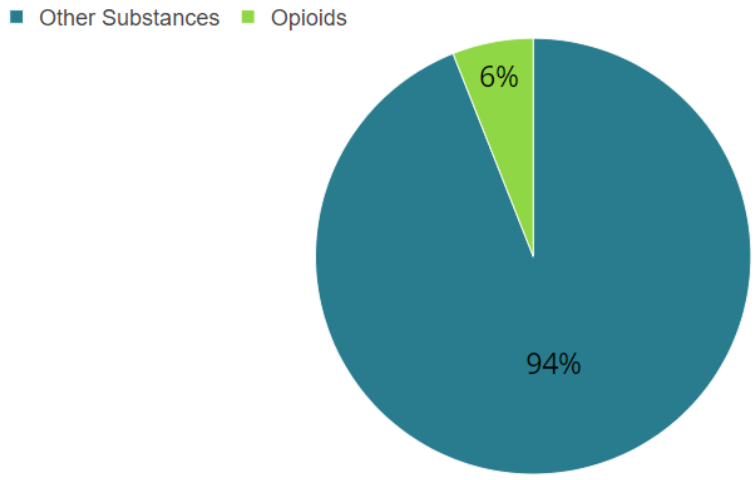
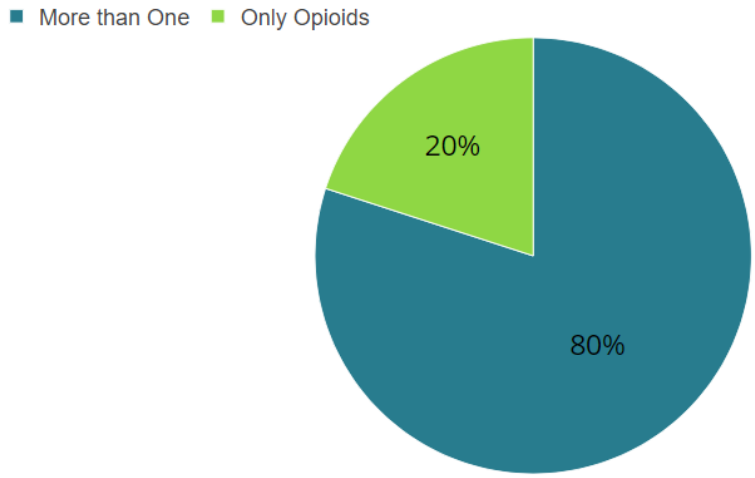
Opioids in Combination with Other Substances

Self-Reported Opioid Use among People Entering Treatment in Iowa, 2000-2018



About this Visualization: The TEDS data set contains over 500,000 treatment episodes in the state of Iowa, ranging from 2000 to 2018. Opioids were reported as being used in only 6 percent of all cases. For the rest of this analysis, we will be using the subset of data where opioid use was reported.

Self-Reported Polysubstance Use among People Entering Treatment for Opioid Use in Iowa, 2000-2018



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Appendix: Data and Methods

Data

A core goal of our evaluation and analytics is to enable nearly real-time monitoring of the landscape of substance use in Iowa. To support Iowa in achieving this goal, we collected, cleaned, analyzed, and modeled five large-scale data sets containing information critical for monitoring substance use. Information on each is presented below.

1. *Treatment Episode Data Set- Admission and Discharges (TEDS), 2000-2018*

Treatment Episode Data Set (TEDS) was collected and distributed by the Substance Abuse and Mental Health Data Archive (SAMHDA). TEDS data provides information about substance abuse treatment episodes within two datasets, admission and discharge. TEDS-Admission (TEDS-A) data have been collected since 1992 and TEDS-Discharges data were first collected and reported in 2000. The TEDS system collects data provided by states to monitor substance abuse treatment from various local, state, and national geographies. Each state provides a minimum dataset and a supplemental dataset. The minimum dataset incorporates 19 items including, client demographics, substances used by the client, route of administration, frequency of use, age of first use, treatment referral source, and service type. The supplemental dataset adds fifteen psychiatric, social, and economic measures.

The TEDS-A dataset used in the Public Science Collaborative (PSC) dashboards combined the 2000-2017 concatenated public use file (PUF) and the 2018 PUF. The data were downloaded on 3/25/2021 from the SAMHSA website (https://www.samhsa.gov/data/data-we-collect/teds-treatment-episode-data-set). These files were appended using Stata (version 17) to create a single dataset containing measures from 2000 to 2018. The national dataset had 37,436,529 observations and included data from all states and territories. A small number of states that did not report key data and were excluded from select years. For further information regarding the exclusion of some states, please consult the TEDS-A codebooks. The national dataset was subset to include 535,351 observations from Iowa. For some of our analysis, we considered substance use patterns for the country as a whole, and in others, we established a data measurement system focused on Iowa's neighboring states. Tracking substance use happenings in states adjacent to Iowa is important because our analysis shows a high degree of associate between, for example, methamphetamine use rates among the treatment seeking population in Council Bluffs Iowa and is across-the river neighboring city of Omaha Nebraska.Put differently, future substance use outbreaks in Iowa are likely to emerge from a nearest neighboring state. There were 3,956,865 observations in the nearest neighbor classification.

Using data from TEDS-A 2000-2018, a statistical model was constructed and tested to identify drug-specific risk factors. We relied on the variables sub1, sub2, and sub3, and the several derived *.flg variables provided by TEDS data administrators to identify and model a specific

substance of use. One record may have up to three of these flagging variables. For example, if an individual reported cocaine on the sub1 question, the cocaine flag would receive a "1." If this same individual reported cocaine use on sub1, methamphetamine use on sub2, and cannabis use on sub3, this record would have a "1" on the cocaine, methamphetamine, and cannabis flagging variables. To identify risk factors associated with each substance, we estimated sets of multi-variate logistic regression models over each of eight substances, including alcohol, benzodiazepine, cannabis, cocaine, heroin, methamphetamine, , and opioids as outcome variables. The model included measures of time, sociodemographic and economic attributes, treatment factors, urbanity, and intravenous drug use. This model helped identify Iowa-specific risks factors for each substance, which informed our selection of data from the American Community Survey for the Substance Use Risk Index dashboard (see pages 4-6).

2. *National Survey on Drug Use and Health data (NSDUH), 2015-2019*

The National Survey on Drug Use and Health (NSDUH) is a national study administered by the Substance Abuse and Mental Health Services Administration (SAMSHSA) that examines the health behaviors and conditions, drug use, and mental health of individuals across the United States. Respondents in the NSDUH are representative of persons aged 12 and over in the noninstitutionalized civilian population of every state, including the District of Columbia. Excluded from the NSDUH are individuals in correctional or mental health facilities, active duty military personnel, and individuals who do not maintain a stable residence. The annual targeted sample size is approximately 70,000 with frequency weighting variables available to enable researchers to generalize to the national population. To address the private nature of the questions asked in the survey, data arecollected using a computer-assisted interviewing method. In 2015, a substantial redesign of sampling and questionnaire led to an expansion in the number of substances specifically included in the variables, making comparisons of some drugs difficult over the pre and post 2015 period. The data were downloaded in a public use file (PUF) from the SAMSHSA website in February, 2021 and included the years 2002-2019 in a single, integrated file. The dataset has 1,005,421 observations and eighteen frequency weighting variables to enable generalization to the United States as a whole. There were 4,741 variables in the original dataset. The data were cleaned and appended in Stata 17. All observations were retained, regardless of their completeness. Using variable crosswalks charts, data were coded to measure every available year.

With these data, we created a statistical model to identify substance use risk factors as observed among the general population in the US. To identify risk factors associated with each substance, we estimated sets of multi-variate logistic regression models over each of eight substances, including alcohol, benzodiazepine, cannabis, cocaine, heroin, methamphetamine, , and opioids as outcome variables. These models included measures of time, sociodemographic and economic attributes, and urbanity. This model provided specific risks factors from each model, which informed our selection of data from the American Community Survey for development of the dashboard.

3. *The United States Census American Community Survey data (ACS), 2015-2019*

The U.S. Census Bureau American Community Survey (ACS) is an annual nationwide survey collecting data on a variety of individual and household attributes. The most recent estimates are for 2019. The 5-year estimates we rely on in this reporting aggregate data from 2015-2019 to offer a larger sample size and lower standard errors (for more details, see https://www.census.gov/programs-surveys/acs/). The 5-year pooled dataset represents 60 months of data that enable more precise multi-year estimates. Because many of Iowa's counties have relatively small populations, the 5-year set of pooled data is the only type of ACS estimates that are available to use across all 99 counties. See the American Community Survey Handbook for Users for more information on pooled, 5-year estimates (https://www.census.gov/programs-surveys/acs/guidance/handbooks/general.html). ACS data was accessed using the Census API, R 4.0.4, and the R package tidycensus (Walker and Herman, 2021). This package also accesses Census TIGER/Line Shapefiles for geographic boundaries. The data was used at the county level and the census tract level.

4. *U.S. Drug Enforcement Administration Automation of Reports and Consolidated Order System (ARCOS), 2006-2014*

The U.S. Department of Justice Drug Enforcement Agency, Automation of Reports and Consolidated Orders System (ARCOS) data includes oxycodone and hydrocodone transactions from distributors to retail locations, and was retrieved from the Washington Post website: https://wpinvestigative.github.io/arcos/. The ARCOS dataset was used for Public Science Collaborative's Prescription Monitoring Program (PMP) dashboard in lieu of restricted prescription data in Iowa that the PSC team was not given access to, when requested through a data sharing request to the Iowa Department of Public Health, Substance Abuse Bureau. Although use of the PMP data is recommended in the OD2A RFP, was detailed in this team's contract for services, and is utilized by many states as an essential element of their Opioid Dashboards, the PMP data have been blocked from distribution in Iowa, even to business agents of the state agency, such as PSC. We strongly urge Iowa's Department of Public Health to seek out stronger legal access and protections to use PMP data to monitor substance use outbreaks, owing to the outsized role that access and supply of opioids has on overdoses and deaths. Failure to incorporate supply-side factors in its data system means leaves prevention monitoring systems are blind to perhaps the most significant risk factor.

The ARCOS data demonstrates possible uses of real-time PMP data, notwithstanding it being 7 years out of date at the time of this writing. The data provided by the Washington Post is from 2006 to 2014 and documents all retail pharmacy locations in Iowa. Each observation in the data file is a transaction, with information about the reporter (distributor), buyer (retail location), drug volume, and transaction date. Retail location latitudes and longitudes were constructed

using the Google Maps API and the R ggmap package. We combined the buyer_address1, buyer_address2, buyer_city, buyer_state, andbuyer_zip columns to create a complete, searchable address that enabled us to obtain location coordinates. After geocoding of the 1363 retail locations in the dataset, six locations were found to have been geocoded outside of the state of Iowa. Because those were identifiable address errors, a manual search for those locations was performed to find their latitudes and longitudes. The visualizations were created using the ARCOS data, aggregating MME amount by buyer_dea_number, buyer_county, and year.

5. *The Iowa Public Health Tracking Portal, Sexually Transmitted Disease data (IDPH STD), 2011-2019*

The Iowa Department of Public Health (IDPH) collects data on the number of sexually transmitted infections in the state of Iowa to meet federal reporting requirements set by the Centers of Disease Control (CDC). Anonymized and clean data files containing some of this information are made publicly available on the Iowa Public Health Tracking Portal (https://tracking.idph.iowa.gov/Health/Sexually-Transmitted-Diseases/About-STD-Data). See the Iowa Department of Public Health data tracking portal for more information on data suppression (https://tracking.idph.iowa.gov/). The 2011-2019 county-level estimates of chlamydia and gonorrhea rates were downloaded from the Iowa Public Health Tracking Portal in February, 2021. The same data has been requested for syphilis (which has higher suppression rates and is not available at the same level of granularity as chlamydia and gonorrhea). The Public Science Collaborative team is awaiting a response to this request. If the data is provided, the STI dashboards will be updated to include this information.

Data on chlamydia and gonorrhea cases were download for each year from 2011 to 2019 and compiled into one file. Information on the county, number of cases, and rate per 100,000 people was obtained for each year. Counties that had zero reported cases in a given year were assigned a rate of zero cases per 100,000 people. Counties that had incomplete reporting data or less than 14 cases in a given year had their rate of cases suppressed. The data is more complete in 2019 than it was in 2011. In 2011, 17 of the 99 counties in Iowa had suppressed rates of chlamydia infections and 82 counties had zero cases or suppressed rates of gonorrhea infections. In 2019, chlamydia infection rates were suppressed in only 5 counties, and 79 counties had suppressed gonorrhea infection rates or zero reported cases. The total change in rate of cases between 2011 and 2019 was calculated and added to the data. If any county had a suppressed infection rate for either 2011 or 2019, the change in rates was suppressed as well. Year-specific maps of the infection rates were created, as well as the overall change in infection rate. Additional visualizations included the trends for every county, the ten largest counties by population, and the ten counties with the highest rate of each infection in 2019. Data manipulation was completed in excel, and visuals were created in R using ggplot2, shiny, and plotly packages.

Methods

The IHIP dashboards were built using RMarkdown, RShiny, and a variety of R packages. Data was cleaned in R (R Core Team, 2021) and Stata 17 (StataCorp, 2021). For geospatial data that required geocoding, points were geocoded using the Google Maps API and R ggmap package (Kahle and Wickham, 2013), and a small number of points were manually geocoded. Most dashboards were first built in RMarkdown but were subsequently published and hosted on RShiny (Chang et al, 2021) and some use RShiny elements for interactivity. The dashboards were created with end users in mind, with an effort to maximize the tools for users to interact with and make use of data visualizations. For that reason, most data visualizations were created using the R ggplot2 package (Wickham et al, 2019), then converted to R Plotly (Sievert, 2020) visualizations for interactivity. The Leaflet package (Cheng et al, 2021) was also used to create some interactive maps. The viridis color palette and R package (Garnier, 2018) were used for every plot that uses a continuous scale for color fill.

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