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Author(s):	Jason Beaman D.O., M.S., M.P.H., FAPA
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Oklahoma Methamphetamine Data Initiative:

Final Research Report

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Jason Beaman D.O., M.S., M.P.H., FAPA

jason.beaman@okstate.edu 918-561-8269

Oklahoma State University Center for Health Sciences

1111 East 17th Street Tulsa, Oklahoma 74107

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Oklahoma Methamphetamine Data Initiative: Final Research Report

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Oklahoma Methamphetamine Data Initiative:

Final Research Report

Abstract

The Oklahoma Methamphetamine Data Initiative (OKMDI) was an NIJ funded project that examined the intersection of methamphetamine and violence. Utilizing various data sources, the study analyzed the relationship between methamphetamine use metrics (overdose deaths, related crimes) and violent crime (rape, assault, robbery, murder). Key objectives included developing a dashboard, analyzing methamphetamine-crime intersections, and assessing the influence of social determinants of health (SDOH) on methamphetamine use. Results showed significant correlations between methamphetamine overdoses and violent crimes, especially economic-compulsive crimes. Geographic variations highlighted distinct patterns in rural and American Indian communities. The results emphasize the complex interplay between methamphetamine use, violent crime, and socio-economic factors, advocating for targeted prevention strategies. The OKMDI provides a robust framework for addressing substance use and violence, offering valuable insights for policymakers and law enforcement; see https://medicine.okstate.edu/academics/psychiatry/ok-methamphetamine-data-initiative.html.

Background and Research Questions

Oklahoma, like many other regions in the United States has been ravaged by the illicit substance methamphetamine (Bonk et al., 2020). At the same time, violence has perpetrated numerous negative consequences on our communities (*Community Violence Prevention*, 2022, *Oklahoma Violent Death Reporting System*, n.d.; Messing et al., 2014). The Oklahoma Methamphetamine Data Initiative (OKMDI) examined the relationship between methamphetamine and violence. The goal for the project is to better inform law enforcement and other stakeholders on upstream prevention.

Major Goals and Objectives

The major objectives of the project included developing a dashboard of relevant information to assist law enforcement; analyzing the relationship between methamphetamine and violent crime; and examining the effects of methamphetamine and violent crime on upstream factors (social determinants of health). In addition to crime and drug overdose information sources, we used Google Trends data to identify search terms in internet searches that may be correlated with methamphetamine use.

Research Questions

The above goals and objectives were synthesized into distinct research questions: Where are methamphetamine use and violent crime intersections more prevalent; are there cultural and geographic differences (e.g., American Indian, and rural communities); are there upstream factors (Social Determinants of Health) that mediate violent crime; and does identifying patterns in traditional and new data aid community surveillance, intervention, and prevention? Finally, questions were asked as to what search terms may be correlated with methamphetamine use and can these terms, combined with other analysis, be used to provide economic forecasting to predict future crimes. These questions are discussed in more detail below.

Research Methods

Variables and Data Sources

The project largely utilized publicly available data in order to answer the research questions and accomplish the goals. The data centered on two broad concepts: “methamphetamine use” and “violence.” It is important to discuss the data that was used to define these two concepts in more detail.

Understanding the use of methamphetamine in a community can be difficult, especially at a geographically relevant level such as a county. Perhaps the best metric (while not perfect) is measuring overdoses. This builds on the premise that communities which have higher rates of methamphetamine use will therefore have higher rates of death. The limitations of this conclusion are discussed at the end of this report.

Fatal methamphetamine overdose numbers are available from the Centers for Disease Control and Prevention (CDC) Wide-ranging Online Data for Epidemiological Research (WONDER). Mortality data from WONDER is derived from states' vital statistics records. WONDER allows users to query county-level mortality rates by cause. Methamphetamine overdose was queried, ICD-10 code T43.6, which is defined as Psychostimulants with Abuse Potential. While this code encapsulates multiple stimulants, it is widely used as a measure for methamphetamine (Drug Enforcement Administration, 2021). Secondary to privacy concerns, WONDER suppresses data in counties with fewer than 10 deaths. For the primary year of analysis, 2625 of 3147 (83.41%) counties had the crude rate of drug overdoses suppressed within the CDC WONDER data, while data from County Health Rankings, which provided a 3-year average of drug overdose mortality rates, had 1427 (45.34%) counties suppressed. To overcome this limitation, two avenues were pursued: first, unsuppressed data was requested from the CDC and was pending at the time of report submission. Second, Multiple Imputation with Chained Equations (MICE) was utilized. MICE is frequently used to address missing data within survey data and with multi-level data and hierarchical designs. Unlike Multiple Imputation (MI), which assumes data is multivariate-normally distributed (MVN), MICE uses specified formulaic algorithms incorporating additional variables within the dataset to create imputations with more precise estimations—especially helpful when working with non-normally distributed and categorical variables. In the case of our results, we present both the complete case analyses as well as the MICE estimated results for all counties with missing data. This is important due to the complete case analysis inherently consisting of counties with unsuppressed counts—counties in which methamphetamine overdoses occur more frequently.

Another metric that can be utilized to understand methamphetamine use in a community is methamphetamine-related crimes (such as possession). Again, the premise is that communities that have higher rates of methamphetamine use will have higher rates of crimes related to such. The limitations of this conclusion are discussed at the end of this report. Data for this metric are available from the Federal Bureau of Investigation (FBI) Uniform Crime Reporting (UCR) and subsequent National Incident-Based Reporting System (NIBRS). Local law enforcement agencies report certain crimes to UCR. This data can then be collated into county level. On a more local level, crime data for the State of Oklahoma can be extrapolated from Oklahoma State Court Network (OSCN). OSCN is an online resource that contains information about courts in Oklahoma, including court dockets, filings by county, legal research, and forms by the Administrative Office of the Court. As it relates to filings, OSCN data contains information such as the case number, county (i.e., where the alleged crime occurred), defendant, attorney, counts, and docket information (i.e., how and whether the defendant was prosecuted). Limitations to the use of this data set are discussed at the end of the report.

The second major concept to explore is "violence." The best available metric for this is through "violent crimes." There are various definitions of violent crime. The definition used for this project was from the National Institute of Justice which states "violent crimes include rape, sexual assault, robbery, assault, and murder" (National Institute of Justice, n.d.). The source of data for this metric was from the above discussed UCR/NIBRS; OSCN was also utilized for state (Oklahoma) level analysis.

Violence from illicit drug use can stem from different reasons. An exceptionally psychoactive substance, such as methamphetamine, could lead to increased interpersonal violence (Brecht & Herbeck, 2013; Foulds et al., 2020). Furthermore, as individuals seek out money in order to obtain the substance, there may be increased rates of other crimes, such as robbery (Gizzi & Gerkin, 2010). Finally, as methamphetamine often involves organized crime, there can be more community violence as different groups battle for distribution rights (Stoneberg et al., 2018). These different types of substance related violence were classified by Goldstein's Drugs/Violence Nexus as psychopharmacologic, economic-compulsive, and systemic (respectively) (Goldstein, 1985). Rape, aggravated assault, and sexual assault were classified as psychopharmacologic crime. Robbery was classified as economic-compulsive, and homicide was classified as systemic crime. The limitations to this classification are discussed at the end of the report.

The final category of data utilized for the project can be broadly categorized as upstream factors. These factors include Social Determinants of Health (SDOH), Adverse Childhood Experiences (ACEs), Indian Country, and urbanicity.

There are five categories of SDOH recognized by the CDC: Healthcare Access and Quality, Education Access and Quality, Social and Community Context, Economic Stability, and Neighborhood and Built Environment. These determinants can be evaluated in different ways. Social and Community Context was evaluated by food insecurity, race, percent of population who smokes or has obesity, and teen birth rate. This data was derived from County Health Rankings (CHR), with the exception of food insecurity which was obtained from Feeding America. CHR is an initiative by the University of Wisconsin that utilizes different datasets to provide metrics for all counties in the U.S. (County Health Rankings & Roadmaps, n.d.). Healthcare Access and Quality was evaluated utilizing the metric of percentage of individuals within the county lacking insurance. This data was derived from CHR. Education Access and Quality was evaluated utilizing high school graduation rate and percent of individuals with "some college." This data was derived from CHR. Economic Stability was evaluated utilizing the metric of percent poverty within the county as listed in CHR. Unemployment rates were also analyzed. This data was obtained from the Local Area Unemployment Statistics (LAUS). Finally, Neighborhood and Built Environment was analyzed utilizing the metric of this poverty percentage, again obtained from CHR.

The CDC provides context for what is classified as adverse childhood experiences. This includes experiencing abuse or neglect, witnessing violence, having a family member attempt or die by suicide, having a parent with substance use or mental health problems, and finally, instability in the house secondary to parental separation or incarceration. Higher ACE scores are quite often associated with negative health outcomes, greater health risk behaviors, and greater socioeconomic challenges (CDC, 2021). It is very difficult to calculate the rates of these events at the county level. Fortunately, this task is in progress at OSU CHS for the State of Oklahoma through the creation of the Oklahoma Adversity Surveillance Index System (OASIS). OASIS is collecting rates of different ACEs in order to better inform policy and prevention. Data for OASIS comes from different sources to measure the ACE prevalence at a societal level, as opposed to the individual level (through surveys). OASIS identifies the following county-level data: divorce, parental substance use, parental mental illness, child abuse, neglect, and domestic violence. This data was used by OKMDI to examine the relationship of ACEs with methamphetamine and violence. OASIS is not without limitations, which are discussed at the end of the report.

Indian Country is the nomenclature used to identify locations in the U.S. that have large populations of Native Americans. Data for this was obtained from the U.S. Environmental Protection Agency. As noted by the EPA, and secondary to a recent U.S. Supreme Court decision (McGirt v. Oklahoma), these boundaries are in flux. Defining Indian Country is not a perfected methodology, and the limitations are discussed at the end of the report.

Urbanicity is the term used to signify counties as either metropolitan (metro) or rural (non-metro). This could be an important distinction due to the difference in social and economic disparities between the areas. To designate the counties as metro or rural, the USDA Economic Research Service was used, which often uses data on nonmetropolitan (nonmetro) areas defined by the Office of Management and Budget (OMB) on the basis of counties or county-equivalent units.

Data Analysis

Each research question was addressed using different datasets. However, the methodology was essentially the same as each question utilized a descriptive cross-sectional research design. For Research Question 1.1, “Where is the intersection of methamphetamine use and violent crime most prevalent across the US?” using data extracted from NIBRS and CDC WONDER, the correlation between methamphetamine-related deaths and violent crimes within communities was analyzed. Heat Maps were created in R 3.6.1 to display the data and identify areas of concern at the state and county level. By obtaining such data, appropriate primary, secondary, and tertiary prevention programs can be established and subsequently evaluated. Statistical analyses were conducted in Stata 16.1. Pearson correlation coefficients were computed to determine if there is a relationship between methamphetamine-related deaths and violent crimes at the state and county level. We completed binary regression using both all violent crimes as indicated by NIBRS as well as psychopharmacological, economic-compulsive, and systemic crimes. Tests were conducted using an alpha of .05. Scatterplots of the variables were reviewed to examine the assumption of linearity. The coefficients of determination (i.e., the effect sizes) were calculated to determine the proportion of the variance in the dependent variable that can be attributed to the independent variable. Correlation coefficients were examined according to the direction and strength of the relationship between methamphetamine-related deaths and violent crimes.

For Research Question 1.2, "Are there cultural and geographic differences, such as communities that are rural or predominantly minority—specifically American Indian and rural communities—that have a higher risk of violent crime related to the use of methamphetamine?" utilizing data extracted from OSCN, OASIS, Feeding America, and LAUS, statistical analyses were conducted in Stata 16.1. Hierarchical regression was used to predict violent crime as a function of methamphetamine use, gender, age, ethnicity, food security, financial risk, and Adverse Childhood Experiences. Further, 'location' was classified as a contextual variable in that violent crime will be allowed to vary depending on the rural versus urban distinction. Hierarchical regression models are appropriate for research designs when the data is organized at more than one level (i.e., nested data). At the lower level, the units of analysis are the individuals which are nested within the contextual unit (upper level). Scores on the dependent variable were adjusted for covariates (e.g. individual differences) before testing for contextual differences.

For Research Question 2.1, "Which upstream factors, including urbanicity and Social Determinants of Health, directly impact or mediate violent crimes in Oklahoma metropolitan, rural, or American Indian communities?," utilizing extracted data from OASIS, OSCN, Feeding America, and LAUS, project staff identified social, cultural, economic, and behavioral factors that are present within communities with a high rate of drug-related violent crime, as well as those identified in the previous research questions. Hierarchical regression was used to narrow the field of variables significantly influential to violent crime. Included variables were then modeled in directional pathways to determine which upstream factors can provide the greatest total effect on methamphetamine-related violent crimes. All individual metrics were incorporated into a single "upstream" metric so as to be able to compare locations to each other and the national average. Hierarchical regression analysis (similar to that proposed in RQ 1.2) was used to identify variables with strong influence on methamphetamine-related violent crimes and was conducted in Stata 16.1. After the most relevant and impactful variables were identified, we used Structural Equation Modeling (SEM) to quantify the relationships. SEM is a multivariate analysis method for simultaneously estimating multiple directional, theory guided relationships between latent constructs and measured variables using regression and factor analytic techniques. Mediating variables in SEM hold their place allowing for examination of the magnitude of direct and indirect effects on the outcome variable. SEM analyses were conducted using R 3.6.1.

Finally, for Research Question 2.2, “Are there identifiable patterns in search engine platforms that precede criminal violence pertaining to methamphetamines that will aid in community surveillance and prevention,” a descriptive longitudinal research design was employed. Publicly available data obtained from Google Trends was used to collect longitudinal data of search volume for methamphetamine-related terms across states and select metropolitan areas, measure their association with monthly violent crime statistics, and use economic forecasting to determine the efficacy of predicting violent crimes. Google Trends search volumes are timeframe and location dependent— thus, data provided is relative to the highest percentage of specific searches to the total volume of queries. Search terms identified from research questions 1.1, 1.2, and 2.1, as well as other terms identified from previous publications to be associated with methamphetamine use were compiled individually and in accordance with the timeframes (daily, weekly, monthly, quarterly) and timespan (from as early as 2004-2020) from data collected related to violent crimes and relevant geographical locations using Google Trends. Given the lag of time between methamphetamine use, criminal activity, and subsequent prosecution, a one-to-three-month delay in datasets was anticipated, and therefore internet activity was adjusted for the lag time. Data collected was transferred to a heat map showing density of and associations between methamphetamine-related search interests and violent crimes. Further, economic forecasting models were created to determine the predictability of future violent crimes based on collected internet searches to determine its viability for use in community surveillance, methamphetamine use, and prevention of violent crimes. After data compilation, bivariate Pearson correlation coefficients between (lagged) internet search volume for specified methamphetamine queries and violent crime were calculated in Stata 16.1. Heatmaps by-state for the U.S. and by metro-area for Oklahoma were created for the most associated search terms. If multiple search terms were relevant, regression models were used for prediction of violent crimes. Using truncated time-series data from either Google Trends search volume or regression estimates, auto-regressive integrated moving average (ARIMA) algorithms (Hyndman & Khandakar, 2008) were used to create forecast models to predict trends of violent crime. ARIMA models forecast predicted values of variables of interest — in this case methamphetamine-related search terms associated with predicated violent crimes — using past values of the variables themselves. Auto-regressive models are flexible in handling many types of time-series patterns including dynamic, seasonal, and irregular changes (Brockwell & Davis, 2016).

Results

Goal 1.1 was to develop procedures and analyses to evaluate the relationship between methamphetamine use and violent crime to create a regularly updated dashboard which can be utilized by law enforcement for strategic deployment of supply side intervention resources. This goal was accomplished using the procedures described above. The Dashboard was created in Tableau and is publicly available (Oklahoma Methamphetamine Data Initiative https://public.tableau.com/app/profile/forrest.gandll/viz/OMDI_US_allMP11/OMDIAnalysis). As the dashboard involves work effort in regular data collection and analysis, it will not be updated past the project period. However, the dashboard provides the foundation and components so that it can serve as a tool to others who wish to create a similar tool. Aside from the dashboard, Goal 1.1 had three objectives. The first objective was to provide a metric for the relationship between crime and methamphetamine use for counties in the U.S. This metric was created by dividing the rate of violent crime per county by the number of overdoses in that county. This is the metric that is available in the dashboard.

The second objective of Goal 1.1 was to classify violence as systemic, economic-compulsive, or psychopharmacologic. The national county-level crude rates of all violent crime, economic-compulsive crime, psychopharmacological crime, and systemic crime are listed in Table 1.

Table 1. Average level crude rates of crime and methamphetamine overdose.

Type of Crime	**County level crude rate**	
	M (SD)	95% CI
All Violent Crime	408.52 (32.71)	344.38-472.66
Psychopharmacological crime (rape, sexual assault, and aggravated assault)	350.25 (7.87)	334.82-365.67
Assault (alone)	328.84 (7.49)	314.16-343.52
Sexual Assault (alone)	19.95 (0.51)	18.95-20.95
Rape (alone)	1.46 (0.07)	1.32-1.59
Economic-compulsive crime (robbery)	9.31 (0.4)	8.53-10.08
Systemic (murder)	15.55 (0.39)	14.79-16.3
Methamphetamine overdoses	36.36 (1.52)	33.28-39.44

We performed statistical regression comparing All Violent Crime with methamphetamine overdose mortalities. Pearson R correlates showed a significant relationship in the adjusted model between methamphetamine overdose mortality and all violent crime at the county level ($F = 5.55$, $P = .005$). A multivariable model comparing economic-compulsive, systemic, and psychopharmacological crimes showed a significant relationship between methamphetamine overdoses and economic-compulsive crimes ($F = 47.60$, $P < .001$; Table 2). The majority of violent crimes were mostly of psychopharmacological typology with an average rate of 349.47 (SE=7.86) per 100,000 people—predominantly from assault. Average county-level rates of Economic-compulsive crime (robbery) was 9.28 (SE = 0.4) and Systemic (murder) was 15.51 (SE = 0.38; Table 2).

Table 2. Regression analyses assessing all violent crime and subsets of crime, methamphetamine overdoses, and urbanicity using complete case and imputed data.						
Variable	**Complete case analysis[A]**			**All counties with imputed data[B]**		
	Adjusted model			Adjusted model		
	Coef. (SE)	T, P	F, P	Coef. (SE)	T, P	F, P
All crime						
Overdose rate	3.46 (1.68)	2.06, .04	2.19, .11	1.23 (.57)	2.17, .035	**5.55, .005**
Rural						
Metro	1 [Ref]	--		1 [Ref]	--	
Non-Metro	-104.77 (100.84)	-1.04, .30		-52.89 (17.59)	-3.01, .003	
Psychopharmacological crime (rape, sexual assault, and aggravated assault)						
Overdose rate	3.13 (1.54)	2.04, .042	2.13, .12	1.15 (1.04)	1.11, .27	2..08, .13
Rural						
Metro	1 [Ref]	--		1 [Ref]	--	
Non-Metro	-91.17 (92.25)	-0.99, .32		-58.79 (-2.34)	-2.34, .02	
Economic-compulsive crime (robbery)						
Overdose rate	0.25 (0.12)	2.07, .039	**3.47, .032**	0.08 (0.03)	2.16, .032	**47.60, < .001**
Rural						
Metro	1 [Ref]	--		1 [Ref]	--	
Non-Metro	-15.85 (7.12)	-2.22, .027		-10.45 (1.04)	-10.02, <.001	
Systemic crime (murder)						
Overdose rate	0.09 (0.06)	1.53, .127	1.95, .14	0.00 (0.04)	0.09, .926	0.45, .64
Rural						
Metro	1 [Ref]	--		1 [Ref]	--	
Non-Metro	2.24 (3.36)	0.67, .504		0.99 (1.15)	0.87, .39	
A. Complete case analysis assessed 522 counties with no suppressed data, comprising 92.72% metro counties. B. Imputed data accounted for suppressed overdoses among 2625 counties—697 (26.55%) metro, and 1928 (73.45%) non-metro—and produced results for all 3147 US counties.						

The third objective of Goal 1.1 was to provide a metric for the relationship between crime and methamphetamine for Oklahoma utilizing OSCN rather than UCR/NIBRS. This was accomplished in a similar manner; by dividing the rate of violent crime from OSCN in a county by the number of overdoses in that county. When these results are compared, it becomes apparent that OSCN rates are higher than UCR/NIBRS. Utilizing national UCR/NIBRS data, the highest counties have a metric of 1.00 (a "1:1 ratio") However, utilizing OSCN data, the top county (Johnston) has a 1.308 ratio. The top five Oklahoma counties are listed in Table 3 below. This is further demonstrated in Figure 1.

Table 3: Top five counties in Oklahoma with most closely intersecting violent crimes per methamphetamine overdose (ie., a 1:1 ratio) in 2019 (in no particular order)	
County, State	**Avg. Violent Crime per Overdose**
Beaver County, OK	0.83
Dewey County, OK	1.20
Oklahoma County, OK	1.20
Murray County, OK	0.71
Johnston County, OK	1.308

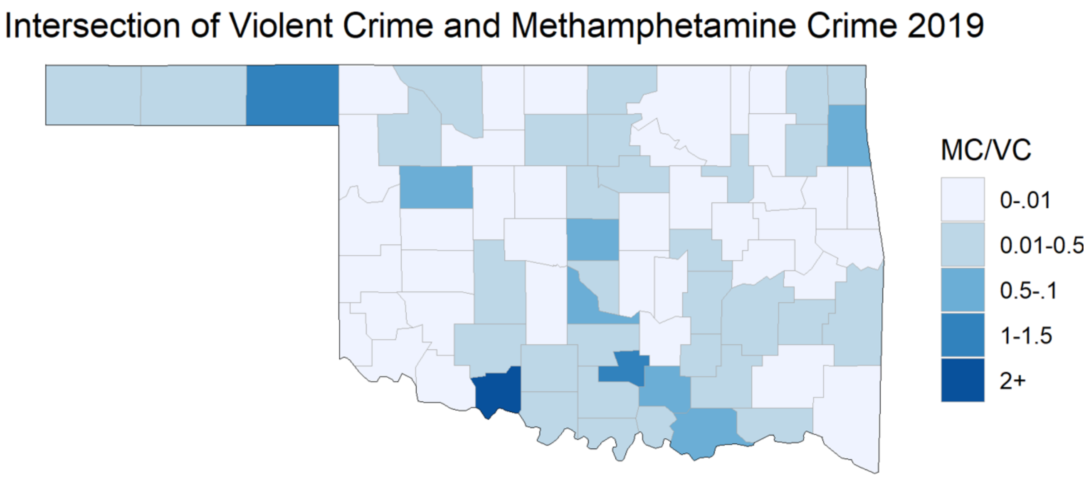

Figure 1. Map of Oklahoma showing 2019 county-level relationship between violent crime and methamphetamine overdose.

In the above graphic, it becomes apparent that there is a central corridor through Oklahoma which appears to follow closely the path of Interstate 35. Further there are consolidations in the panhandle, south central, southeast and northeast. Each consolidation could demonstrate a different distribution cell.

The goal for 1.2 also involved a dashboard. This dashboard addressed four objectives. The first objective was to evaluate the relationship between crime and methamphetamine by urbanicity and type of violence (systemic, economic-compulsive, or psychopharmacologic) utilizing national UCR/NIBRS data. The results are listed in Table 2.

The second objective of Goal 1.2 was to analyze the findings by Indian Country status. Regression models showed that there was not a significant difference in county-level violent crime rate between counties with a tribal designation compared to other counties in both the binary (coef: -3.40, SE=9.33; t=-0.37, P=.72) and adjusted models (coef: -6.08, SE=8.46; t=-0.72, P=.47). The results are listed below in Table 4:

Table 4. Social determinants of health among counties with federal designation as Native Land and those without.

	Counties without federal designation as Tribal	Counties with federal designation as Tribal	Missing	Binary Regression Model	
No. of counties	2594 (82.40)	554 (17.60)	-	Coeff (SE)	t, p
Violent crime rate	252.87 (3.96)	247.34 (7.80)	197 (6.26)	-3.4 (9.33)	-0.37, .72
Unemployment Rate	3.90 (1.33)	4.46 (1.94)	12 (0.38)	0.57 (0.07)	8.31, <.001
Poverty %	14.43 (5.84)	14.57 (5.60)	7 (0.22)	0.14 (0.27)	0.5, .62
Smoking	17.95 (3.47)	17.48 (4.33)	7 (0.22)	-0.47 (0.17)	-2.77, .006
Teen Birth Rate	31.83 (14.74)	33.31 (16.65)	151 (4.8)	1.07 (0.72)	1.47, .14
Food Insecurity	13.70 (4.28)	13.67 (3.70)	6 (0.19)	-0.03 (0.2)	-0.15, .88
Uninsured Rate	11.75 (5.10)	12.86 (5.12)	7 (0.22)	1.1 (0.24)	4.6, <.001
Graduation Rate	89.07 (6.88)	84.64 (8.98)	105 (3.34)	-4.22 (0.35)	-11.96, <.001
Obesity	32.17 (4.55)	31.61 (4.74)	7 (0.22)	-0.56 (0.21)	-2.6, .009
Drug Overdose Mortality Rate	22.13 (12.15)	19.11 (8.42)	1428 (45.36)	-1.29 (0.76)	-1.71, .09
Rural	1560 (60.14)	406 (73.42)	1 (0.03)		

The third and fourth objectives are essentially the same as the first two but using OSCN data instead of UCR. The differences between rural and metro counties within Oklahoma are listed in Table 5 below. Table 6 shows that there was no significant relationship between violent crime and drug overdose mortality rates from National County Health Rankings (top) nor with other methamphetamine-related crimes using OSCN data (bottom).

Table 5. Court filings of criminal activity from the Oklahoma State Court Network between metro and non-metro Oklahoma counties.		
	Metro	non-Metro
# of counties	18 (23.38)	59 (76.62)
Methamphetamine related crime rates		
Delivery	0	0.12 (.93)
Distribution	1.45 (.10)	1.14 (.50)
Maintaining	.10 (.41)	0
Manufacturing	.01 (.03)	0
Possession	96.21 (233.58)	40.67 (77.23)
Trafficking	6.15 (10.40)	4.6 (15.18)
All	102.60 (27.99)	46.50 (87.83)
Violent crime rates		
Assault	353.56 (312.49)	382.86 (155.08)
Homicide	8.21 (6.43)	9.82 (25.26)
Rape	10.60 (12.41)	15.92 (14.94)
Robbery	12.90 (11.03)	12.65 (19.25)
Sexual Assault	5.88 (5.59)	11.45 (21.54)
All	391.15 (335.02)	432.70 (169.13)

Table 6. Associations between violent crime, drug overdose mortality rate (top; county health rankings), and methamphetamine crimes (bottom; OSCN) controlling for urbanicity in Oklahoma

	Adjusted model		
Var.iable	Coef. (SE)	T, P	F (3, 76)
Methamphetamine Overdoses	-2.01 (3.07)	-.66, .52	
Rural			
Metro	1 [Ref]	--	
Non-Metro	-52.88 (50.10)	-1.06, .30	1.19, .31
			F (2, 74)
Methamphetamine Crimes	-.22 (.13)	-1.74 (.09)	
Rural			
Metro	1 [Ref]	--	
Non-Metro	-116.45 (40.06)	-2.91, .005	5.00, .009

Goal 2.1 involved developing the procedures to evaluate the upstream factors (Social Determinants of Health, SDOH) and methamphetamine-related crime and apply that to a dashboard. This goal had four objectives. The first objective was to provide an upstream metric for counties in the U.S. This metric was applied to the above metric in order to determine where

the strongest correlation between methamphetamine and violent crime was with upstream factors. Figure 2 shows our preliminary pathways for upstream factors of methamphetamine use and violent crime, and mediating variables. The results (coefficients) are shown in Table 7.

Table 7. Path analysis of county-level upstream and downstream factors that mediate violent crime.

	Unstandardized		Standardized		*P*
	Coef	SE	Coef	SE	
Violent Crime Rate on					
Average Unemployment	-6.655	4.25	-0.043	0.028	0.12
Drug Overdose Mortality Rate	-0.588	0.409	-0.034	0.024	0.15
Urbanicity	-111.497	10.039	-0.28	0.024	<.001
Food Insecurity %	1871.033	171.261	0.32	0.028	<.001
Drug Overdose Mortality Rate on					
Average Unemployment	1.242	0.252	0.139	0.028	<.001
Food Insecurity %	45.148	9.655	0.132	0.028	<.001
Average Unemployment on					
Urbanicity	0.611	0.062	0.235	0.023	<.001
Food Insecurity % on					
Average Unemployment	0.043	0.004	1.658	0.141	<.001

Goodness of fit: RMSEA = .038, P = .582, Comparative Fit Index (CFI) = 0.998, Tucker-Lewis Index (TLI) = 0.979, showing the model is a good fit to the data.

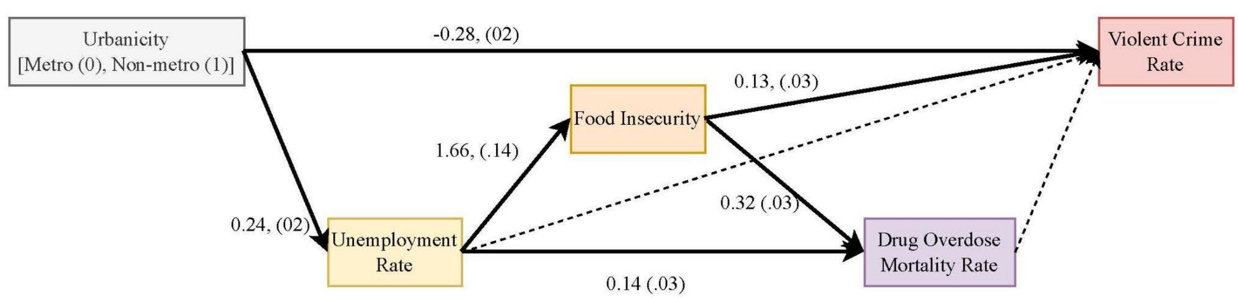

Figure 2. Path analysis showing upstream and downstream impacts on county-level violent crime rates (n=1667; counties with unsuppressed data). *Solid lines indicate statistically significant pathways.

Our preliminary path analysis demonstrates the "upstream metric" of county-level unemployment rate having a significant effect on both food insecurity and drug overdose mortality rates, and that the further downstream factor of food insecurity (the result of unemployment has both a significant direct effect on violent crime). Living in a rural county was significantly related to an increased unemployment rate—a likely driver for methamphetamine use given the known areas most significantly impacted by methamphetamine use.

Further analysis of the different SDOH and the intersection of methamphetamine and violent crime is listed in Table 8. Our hierarchical model showed that the relationship of rates of drug overdose mortality and violent crime did not vary among states (random effects), thus showing that a hierarchical model was not warranted. However, this model did show several SDOH variables were significantly associated (Unemployment rate, Food insecurity %, Graduation %, Poverty %, Household Income, Smokers, Obese, and Metro) with violent crime rates.

Table 8. Hierarchical model assessing social determinant of health at the county level (level 1) nested within States (level 2) and their impact on violent crime rate.

Fixed effects					
Violent Crime	**Coef.**	**Std. Err.**	**t**	**P>t**	**95%CI**
Drug overdose mortality rate	5.54	3.02	1.84	0.07	(-0.37-11.45)
Unemployment rate	-36.75	32.96	-1.11	0.27	(-101.34-27.85)
Food insecurity %	-1042.09	2068.36	-0.50	0.61	(-5096-3011.83)
Graduation %	-27.62	4.95	-5.59	0.00	(-37.32--17.93)
Poverty %	72.23	11.46	6.30	0.00	(49.77-94.7)
Household Income	0.01	0.00	1.93	0.05	(0-0.02)
Smokers	-75.02	18.41	-4.08	0.00	(-111.1--38.94)
Obese	-47.78	9.97	-4.79	0.00	(-67.34--28.23)
Metro	783.46	74.44	10.52	0.00	(637.56-929.36)
Random Effects					
State	**Estimate**	**Std. Err.**	**95%CI**		
sd(_cons)	338.17	56.67	(0-0)		
sd(Residual)	1649.99	21.68	(0-0)		
Model: F(9, 6.9e+06) = 33.77, *P* = < .0001					
**ICC=0.050. ICC is approaching 0, a simple regression is warranted.					

In evaluating the different SDOH, we first examined unemployment. We performed a cross-sectional analysis of unemployment at the county level and methamphetamine overdose mortality. Among the 3,147 U.S. counties available for analysis in 2019, 1,181 were classified as metro and 1,966 were non-metro. Counties in which data for methamphetamine overdoses were available in the CDC WONDER dataset (n=522), were predominantly metro counties (484, 92.72%). Mean rates of unemployment were 3.74 (SD=1.19) for metro counties and 4.16 (SD=1.60) for non-metro counties. Among the counties with suppressed data, (n=2625 counties), 697 (26.55%) were metro and 1928 (73.45%) were non-metro.

Complete case analysis showed a statistically significant relationship between methamphetamine overdoses and both unemployment and urbanicity in the bivariate and multivariable models (Table 9). Using the imputed data which included all counties and accounted for a greater proportion of non-metro counties, the bivariate models showed there was a statistically significant increase in county-level rates of methamphetamine overdoses with increased unemployment (Coef: 4.09, SE=0.50; *P* <.001), and that non-metro counties had overdose rates 5.76 (SE=1.20, *P* <.001) points higher than metro-counties. The multivariable model showed that for every 1-point increase in the county-level unemployment rate, there was a 3.9 (SE=0.51, *P* <.001) point increase in the rate of methamphetamine overdoses when controlling for urbanicity.

Table 9. Regression analysis assessing methamphetamine overdoses, unemployment, and urbanicity using complete case and imputed data.

Variable	**Complete case analysis**[A]			**All counties with imputed data**[B]		
	Adjusted model			Adjusted model		
	Coef. (SE)	T, P	F (2, 517)	Coef. (SE)	T, P	F (2, 26.3)
Unemployment	2.4 (0.53)	4.51, <.001	43.57, <.0001	3.9 (0.51)	7.63, <.001	45.55, <.0001
Rural						
Metro	1 [Ref]	--		1 [Ref]	--	
Non-Metro	18.3 (2.46)	7.43, <.001		4.14 (1.21)	3.42, 0.003	
_cons	14.7 (2.09)	7.02, <.001		11.33 (2.38)	4.77, <.001	

A. Complete case analysis assessed 522 counties with no suppressed data, comprising 92.72% metro counties. B. Imputed data accounted for suppressed overdoses among 2625 counties—697 (26.55%) metro, and 1928 (73.45%) non-metro—and produced results for all 3147 US counties.

Complete case analysis also showed a statistically significant relationship between methamphetamine overdose mortality, unemployment, and violent crime when controlling for urbanicity (Table 10). Using the imputed data which included all counties and accounted for a greater proportion of non-metro counties, the bivariate models showed there was a statistically significant increase in county-level rates of methamphetamine overdoses with increased unemployment and violent crime (Coef: 14.56, SE=0.50; P <.001). The multivariable model showed that for every 1-point increase in the county-level unemployment rate, there was a 3.9 (SE=0.51, P <.001) point increase in the rate of methamphetamine overdoses when controlling for urbanicity.

Table 10. Associations between violent crime, methamphetamine overdoses, unemployment, and urbanicity using complete case and imputed data.						
Variable	**Complete case analysis**[A]			**All counties with imputed data**[B]		
	Adjusted model			Adjusted model		
	Coef. (SE)	T, P	F (3, 516)	Coef. (SE)	T, P	F (3, 333)
Methamphetamine Overdoses	4.40 (1.71)	2.58, .01	3.86, 0.009	2.12 (.63)	3.38, .002	14.56, <.0001
Unemployment	-55.89 (21.10)	-2.65, .008		-38.85 (6.34)	-6.12, <.0001	
Rural						
Metro	1 [Ref]	--		1 [Ref]	--	
Non-Metro	-86.96 (100.71)	-0.86, .388		-41.81 (17.58)	-2.38, .017	
A. Complete case analysis assessed 522 counties with no suppressed data, comprising 92.72% metro counties. B. Imputed data accounted for suppressed overdoses among 2625 counties—697 (26.55%) metro, and 1928 (73.45%) non-metro—and produced results for all 3147 US counties.						

The second objective was to repeat the analysis but to add the layer of urbanicity. When this was performed, the results showed that there was a significant relationship—with rural communities having lower rates of violent crimes (Table 10): The third objective was to add the assessed counties within Indian Country. A bivariate assessment of counties with tribal designation did not have a statistically significant difference in the violent crime rates (Coef -3.4, SE=9.33, P = .72. Additionally, relationships within Indian Country are discussed below.

The fourth objective for Goal 2.1 was to provide the upstream analysis to Oklahoma counties utilizing OSCN data instead of UCR/NIBRS. The results are listed in Table 11 below.

Table 11. County-level associations between violent crime, methamphetamine crime, and social determinants of health within Oklahoma		
	Bivariate Models	Adjusted model

Variable	Coeff (SE)	t, p	Coeff (SD)	t, p
Methamphetamine crimes	0.44 (0.18)	**2.47, .016**	0.51 (0.17)	**2.94, 0.004**
Unemployment Rate	50.64 (25.21)	2.01, 0.048	14.72 (39.91)	0.37, 0.713
Poverty %	11.66 (5.55)	2.1, 0.039	-0.01 (9.53)	0, 0.999
Smoking	25.35 (9.85)	**2.57, 0.012**	12.61 (17.75)	0.71, 0.48
Teen Birth Rate	5.7 (2.04)	2.8, 0.007	3.56 (2.6)	1.37, 0.174
Food Insecurity	16.03 (8.93)	1.79, 0.077	2.14 (17.61)	0.12, 0.904
Uninsured Rate	10.78 (9.07)	1.19, 0.238		
Graduation Rate	2.22 (6.65)	0.33, 0.739		
Obesity	11.36 (9.96)	1.14, 0.257		
American Native Pop. %	4.25 (2.99)	1.42, 0.159		
Asian Pop. %	-54.76 (24.99)	-2.19, 0.032	-27.57 (26.01)	-1.06, 0.293
Black Pop. %	0.92 (7.31)	0.13, 0.9		
Hispanic Pop. %	-0.92 (3.4)	-0.27, 0.787		
NHOPII Pop. %	93.33 (69.01)	1.35, 0.18		
White Pop. %	-2.98 (2.62)	-1.14, 0.258		

After evaluating the SDOH of unemployment, education was examined. A bivariate linear regression model showed there was no significant relationship between violent crime and methamphetamine overdose mortality or high school graduation rate (Table 12) at the county level, when controlling for poverty and urbanicity. We did, however, find a significant relationship between the % of individuals within a county having attended 'some college' and violent crime—with both the complete case analysis and the MICE estimations (Table 13).

Table 12. Associations between violent crime, methamphetamine overdoses, high school graduation rate, and urbanicity using complete case and imputed data.

Variable	**Complete case analysis[A]**			**All counties with imputed data[B]**				
Methamphetamine Overdoses	1.84 (1.73)	1.06, .289	F (4, 517) 4.14, .003	0.27 (0.87)	.31, .76	1.13 (1.22)	0.93, .355	F (4, 689) 2.44, .046
HS graduation rate	5.31 (4.46)	1.19, .234		-2.61 (1.12)	-2.32, .02	-2.32 (1.20)	-1.94, .053	
Poverty (%)	22.96 (6.63)	3.46, .001		1.60 (1.44)	1.11, .266	1.22 (1.87)	0.65, 0.51	
Rural								
Metro	1 [Ref]	--		1 [Ref]	--	1 [Ref]	--	
Non-Metro	155.80 (101.19)	-1.54, .12		-46.39 (17.23)	-2.69, .007	-69.42 (25.89)	-2.68, .008	

A. Complete case analysis assessed 522 counties with no suppressed data, comprising 92.72% metro counties. B. Imputed data accounted for suppressed overdoses among 2625 counties—697 (26.55%) metro, and 1928 (73.45%) non-metro—and produced results for all 3147 US counties.

Table 13. Associations between violent crime, methamphetamine overdoses, percent with some college (or more), and urbanicity using complete case and imputed data.

Variable	Complete case analysis[A]			All counties with imputed data[B]		
	Adjusted model			Adjusted model		
	Coef. (SE)	T, P	F (4, 517), 4.96, .037	Coef. (SE)	T, P	F (4, 720) 2.55, 0.38
Methamphetamine Overdoses	2.6 (1.74)	1.49, 0.136		1.09 (1.21)	0.9, 0.371	
Some College	7.15 (3.33)	2.15, 0.032		1.99 (0.9)	2.21, 0.027	
Poverty (%)	26.08 (6.7)	3.89, 0		4.23 (1.97)	2.14, 0.032	
Rural						
Metro	1 [Ref]	--		1 [Ref]	--	
Non-Metro	-109.17 (101.37)	-1.08, 0.282		-64.58 (26.22)	-2.46, 0.014	

A. Complete case analysis assessed 522 counties with no suppressed data, comprising 92.72% metro counties. B. Imputed data accounted for suppressed overdoses among 2625 counties—697 (26.55%) metro, and 1928 (73.45%) non-metro—and produced results for all 3147 US counties.

Social and Community Context was evaluated by food insecurity, race, percent of population who smokes or has obesity, and teen birth rates. The results were a product of our hierarchical regression assessment and results are listed in Table 14.

Table 14. Hierarchical model assessing social determinant of health at the county level (level 1) nested within States (level 2) and their impact on violent crime rate.

Fixed effects					
Violent Crime	**Coef.**	**Std. Err.**	**t**	**P>t**	**95%CI**
Drug overdose mortality rate	5.54	3.02	1.84	0.07	(-0.37-11.45)
Unemployment rate	-36.75	32.96	-1.11	0.27	(-101.34-27.85)
Food insecurity %	-1042.09	2068.36	-0.50	0.61	(-5096-3011.83)
Graduation %	-27.62	4.95	-5.59	0.00	(-37.32--17.93)
Poverty %	72.23	11.46	6.30	0.00	(49.77-94.7)
HouseholdIncome	0.01	0.00	1.93	0.05	(0-0.02)
Smokers	-75.02	18.41	-4.08	0.00	(-111.1--38.94)
Obese	-47.78	9.97	-4.79	0.00	(-67.34--28.23)
Metro	783.46	74.44	10.52	0.00	(637.56-929.36)
Random Effects					
State	**Estimate**	**Std. Err.**	**95%CI**		
sd(_cons)	338.17	56.67	(0-0)		
sd(Residual)	1649.99	21.68	(0-0)		
Model: F(9, 6.9e+06) = 33.77, P = < .0001					
**ICC=0.050. ICC is approaching 0, a simple regression is warranted.					

The fifth and final objective was to apply the upstream metric to Indian Country in Oklahoma. Table 15 shows differences between counties with and without a federal Tribal designation. Table 16 shows the adjusted relationship between Tribal affiliation and rates of violent crime adjusting for drug overdose mortality rates and other SDOH. Within this model, multiple SDOH were significantly associated with violent crime including socioeconomic status (unemployment rate, uninsured rate, graduation rate), smoking, teen birth rate, food insecurity, urbanicity, and drug overdose mortality rate.

Table 15. Social determinants of health among counties with federal designation as Native Land and those without.

	Counties without federal designation as Tribal	Counties with federal designation as Tribal	Missing	Binary Regression Model	
# of counties	2594 (82.40)	554 (17.60)	-	Coeff (SE)	t, p
Violent crime rate	252.87 (3.96)	247.34 (7.80)	197 (6.26)	-3.4 (9.33)	-0.37, .72
Unemployment Rate	3.90 (1.33)	4.46 (1.94)	12 (0.38)	0.57 (0.07)	8.31, <.001
Poverty %	14.43 (5.84)	14.57 (5.60)	7 (0.22)	0.14 (0.27)	0.5, .62
Smoking	17.95 (3.47)	17.48 (4.33)	7 (0.22)	-0.47 (0.17)	-2.77, .006
Teen Birth Rate	31.83 (14.74)	33.31 (16.65)	151 (4.8)	1.07 (0.72)	1.47, .14
Food Insecurity	13.70 (4.28)	13.67 (3.70)	6 (0.19)	-0.03 (0.2)	-0.15, .88
Uninsured Rate	11.75 (5.10)	12.86 (5.12)	7 (0.22)	1.1 (0.24)	4.6, <.001
Graduation Rate	89.07 (6.88)	84.64 (8.98)	105 (3.34)	-4.22 (0.35)	-11.96, <.001
Obesity	32.17 (4.55)	31.61 (4.74)	7 (0.22)	-0.56 (0.21)	-2.6, .009
Drug Overdose Mortality Rate	22.13 (12.15)	19.11 (8.42)	1428 (45.36)	-1.29 (0.76)	-1.71, .09
Rural	1560 (60.14)	406 (73.42)	1 (0.03)		

Regression models showed that there was not a significant difference in county-level violent crime rate between counties with a tribal designation compared to other counties in both the binary (coef: -3.40, SE=9.33; t=-0.37, *P*=.72) and adjusted models (coef: -6.08, SE=8.46; t=-0.72, *P*=.47).

Table 16. Adjusted regression model for associations between violent crime, Tribally affiliated counties, and SDOH.

	Adjusted Regression Model	
Variable	Coeff (SE)	t, p
Tribal County	-6.08 (8.46)	-0.72, 0.47
Unemployment Rate	-14.5 (2.98)	-4.86, <.001
Uninsured Rate	-1.74 (0.83)	-2.09, 0.037
Graduation Rate	-5.22 (0.47)	-11, <.001
Poverty %	-0.47 (1.15)	-0.4, 0.69
Drug Overdose Mortality Rate	1.17 (0.35)	3.38, 0.001
Smoking	-4.75 (1.43)	-3.31, 0.001
Obesity	-0.28 (0.85)	-0.33, 0.74
Teen Birth Rate	2.72 (0.36)	7.64, <.001
Food Insecurity	19.5 (1.22)	16, <.001
Rural	-90.99 (6.69)	-13.6, <.001

The other category of "upstream factor" was ACEs. The results of these analyses are listed in the two tables below. Table 17 shows the association of crime, methamphetamine use, and ACEs utilizing NIBRS data for violent crime. Table 18 demonstrates the same association. However, in this analysis, OSCN was used to determine rates of violent crime instead of NIBRS.

Table 17. Associations between violent crime reported within the NIBRS, crime involving methamphetamine possession from Oklahoma States Court Network (OSCN), and adverse childhood experiences in Oklahoma using the OASIS project.				
	Bivariate Models		Adjusted model	
	Coef. (SE)	T, P	Coef. (SE)	T, P
Methamphetamine Crimes	-0.16 (0.29)	-0.56, 0.576	0.14 (0.26)	0.52, 0.608
Oklahoma ACEs	0.04 (0.02)	**2.25, 0.028**	0.01 (0.02)	0.33, 0.739
Poverty	34.22 (7.51)	**4.55, 0**	27.71 (9.21)	**3.01, 0.004**
Rural				
Metro	1 [Ref]	--	1 [Ref]	--
Non-Metro	265.92 (81.95)	**3.24, 0.002**	162.28 (83.71)	**1.94, 0.056**

Table 18. Associations between violent crime reported within the Oklahoma States Court Network (OSCN), crime involving methamphetamine possession from OSCN, and adverse childhood experiences in Oklahoma using the OASIS project.				
	Bivariate Models		Adjusted model	
	Coef. (SE)	T, P	Coef. (SE)	T, P
Methamphetamine Possession	0.54 (0.19)	**2.87, 0.005**	0.65 (0.19)	**3.5, 0.001**
Oklahoma ACEs	0.01 (0.01)	1.17, 0.246	0 (0.01)	0.27, 0.786
Poverty	11.66 (5.55)	**2.1, 0.039**	13.78 (6.46)	**2.13, 0.036**
Rural				
Metro	1 [Ref]	--	1 [Ref]	--
Non-Metro	41.55 (58.72)	0.71, 0.481	21.97 (58.71)	0.37, 0.709

Goal 2.2 was to identify search terms and trends that could aid in the prediction of methamphetamine and violence. This was accomplished through two different objectives. The first was to develop a list of search terms that are correlated with methamphetamine use. From the literature search and from external sources, we identified 55 terms in addition to 'methamphetamine' as related to methamphetamines and use of methamphetamine-type drugs (Table 19).

Table 19: Search terms related to methamphetamine use.		
Batu	Getting scattered or spun out	Shabu
Biker's Coffee	Go-Fast	Shards
Black Beauties	Hanyak	Speed
Blade	Hiropon	Stove Top
Chalk	Hot Ice	Super Ice
Chicken Feed	Hot rolling	Tina
Chicken flipping	Ice	Trash
Christina	Kaksonjae	Tweak
Cookies	L.A. Glass	Tweaking
Cotton candy	L.A. Ice	Uppers

Crank	Meth	Ventana
Cristy	Methlies	Vidrio
Crystal	No doze	Wash
Crystal Glass	Pookie	White cross
Crystal Meth	Poor Man's Cocaine	Yaba
Dunk	Quartz	Yellow Bam
Gak	Quick	zooming
Getting fried or foiled	Rocket fuel	
Getting geared up	Scooby snax	

The second objective was to provide economic forecasting models to determine the predictability of methamphetamine-related crimes. Our research frame target dates for the purpose of this objective within this grant was between 01/01/2019 through 07/31/2021 in the state of Oklahoma. We used multiple sources to identify methamphetamine-related crimes in Oklahoma that included arrests and distributable amounts of methamphetamines shown in Table 20.

Table 20. Methamphetamine related crime with arrests in Oklahoma.

Date	State	City	Amount (lbs)	Arrests
02/20/2019	OK	Tulsa	2	2
8/14/19	OK	Bartlesville	60	2
10/16/2020	OK	Grove	231	5
11/4/2020	OK	Muscogee	100+	19
01/14/2021	OK	OKC	151	2
1/29/2021	OK	Tulsa	100	3
03/05/2021	OK	OKC	1050	18
3/17/2021	OK	Tulsa	100	1
03/25/2021	OK	Durant	10+	13
3/28/2021	OK	OKC	7	15
4/15/2021	OK	Spencer	100+	25
6/23/2021	OK	Lawton	12	18
06/23/2021	OK	Poteau	66	2+
07/31/2021	OK	McCurtain	4.5	1

We performed word searches within Twitter from the timeframe 07/01/2020 through 07/31/2021 to identify tweets containing the words from the list above. Twitter searches were limited to a 12-month period. Figure 3 shows the most prevalent words found (cotton candy, crank, crystal, meth, and tweak or tweaking) within Oklahoma and the arrest and size of drugs confiscated during the stop.

We searched each term using Google Trends. Figure 4 shows the trends of the term most commonly searched (methamphetamine) in Oklahoma and dates of arrests with large amounts of drugs confiscated. We found that there were no significant increases in tweets or search interest prior to the arrests being made. From the ARIMA model, the only date within the timeframe of interest—and having the highest search interest for ‘Methamphetamine’— occurred during the week of May 2, 2021, but did not preclude any major arrest for drug related crimes. This spike in search interest was most likely related to a sentencing for two men from a 2018 methamphetamine related arrest (https://www.justice.gov/usao-ndok/pr/two-tulsa-men-sentenced-separate-methamphetamine-distribution-cases). Of additional interest, the trend in search interest from 01/01/2018 to 04/01/2022 showed a decreasing trend (-0.0171*x + 812; R^2 = .342).

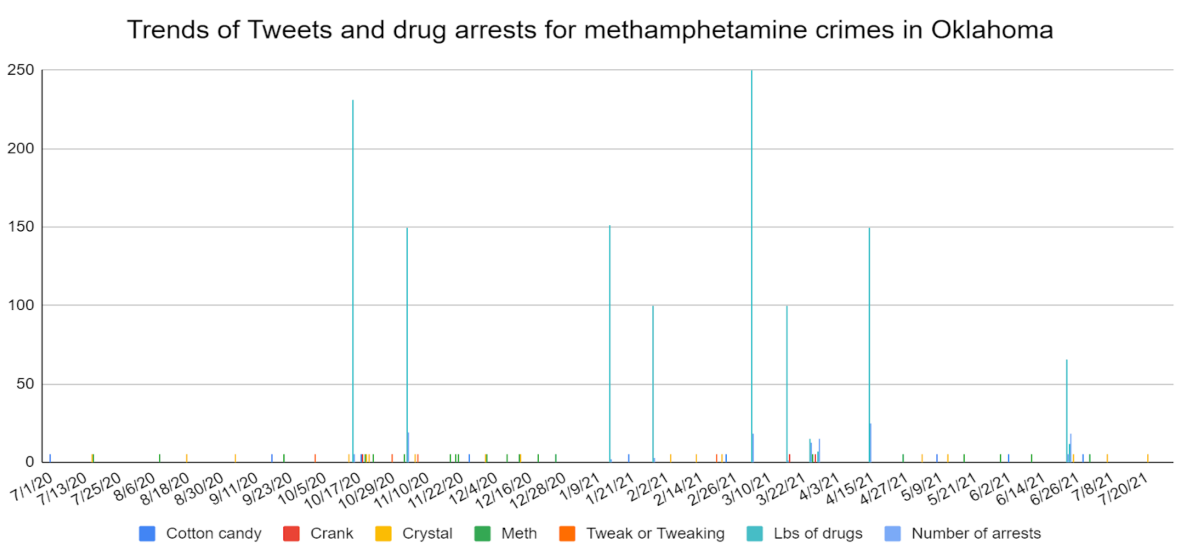

Figure 3. Trends of tweets and methamphetamine crimes in Oklahoma from 07/01/2020 to 07/20/2021.

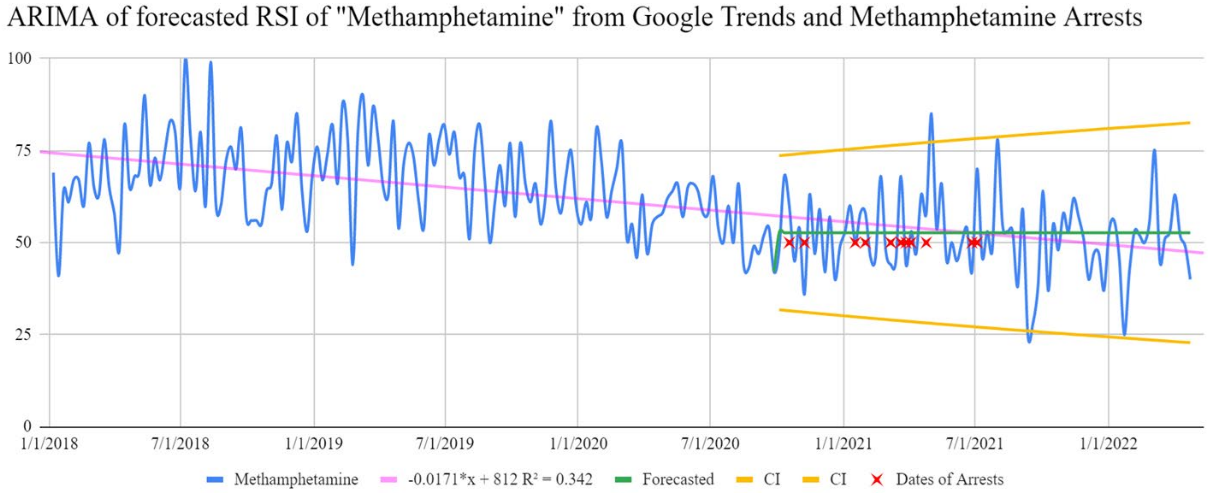

Figure 4. Google trends analysis showing weekly search interest in 'methamphetamine' and 'crystal meth' from 01/01/2018 to 04/01/2022 and forecasted values with confidence intervals from ARIMA modeling.

The above Goals and Objectives correspond to the research questions. Research Question 1.1 was, "Where is the intersection of methamphetamine use and violent crime most prevalent?" The answer to this question is demonstrated in Table 21 below. Further, a screenshot (Figure 5) of the dashboard helps to visualize the distribution.

Table 21. 5 counties most closely intersecting (ie., a 1:1 ratio) with the number of violent crimes per methamphetamine overdose in 2019 (in no particular order)	
County, State	**Avg. Violent Crime per Overdose**
Stanton County, KS	1.00
DeKalb County, MO	1.00
Leflore County, MS	1.00
Hamilton County, NY	1.00
Clay County, TN	1.00

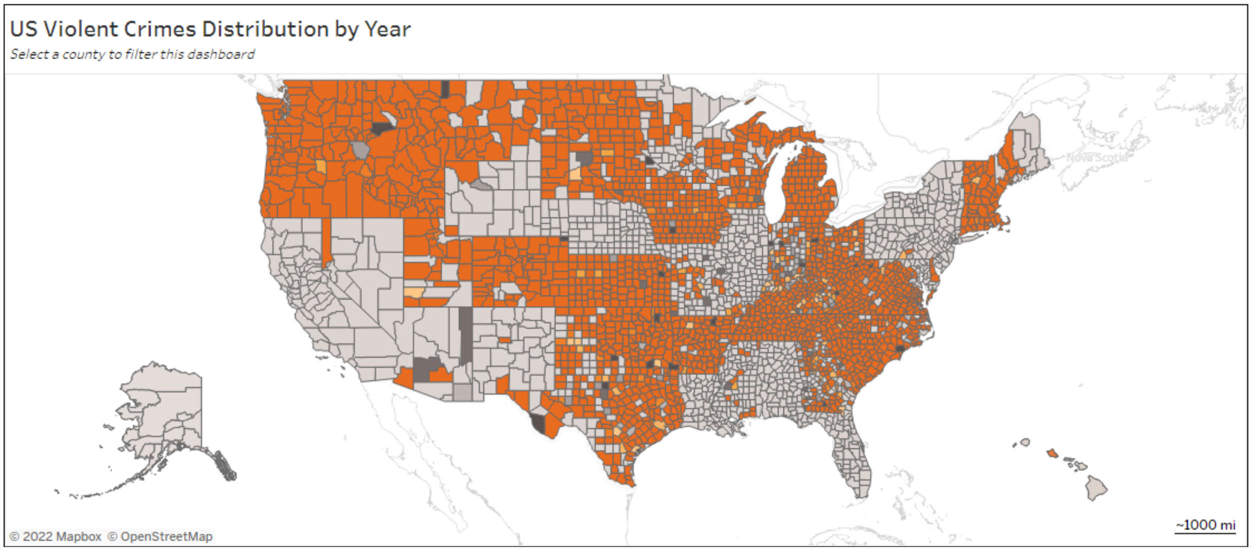

Figure 5. Map of U.S. showing 2019 county-level relationship between violent crime and methamphetamine overdoses (screengrab from public facing dashboard)

Research Question 1.2 asked, “Are there cultural and geographic differences, such as communities that are rural or predominately minority— specifically American Indian and rural communities that have a higher risk of violent crime related to the use of methamphetamine?”

The results indicate that obesity rates, smoking rates, and percent of individuals attending at least some college were significantly associated with violent crime. County urbanicity was significantly associated with violent crime being lower in rural counties. Racial composition of counties was not significantly associated with violent crime rates.

Research Question 2.1 asked, “Which upstream factors directly impact violent crime in Oklahoma metropolitan, rural, and American Indian communities?” Unemployment was likely the largest single modifiable upstream factor in predicting violent crime rate and drug overdose mortality rates. This was shown by its high coefficient and level of significance (<.001) as presented in Tables 9 and 10. This upstream factor predicted an increase in drug overdose mortality rate and food insecurity rates within our path analysis—the latter (food insecurity) having a significant direct effect on violent crime. The increase in violent crime is likely associated with an individual becoming increasingly desperate as their basic needs (food access) are not being met. Within counties with Federal Tribal designations, unemployment was also significantly associated with violent crimes, as well as rates of smoking, obesity, uninsured individuals, and high school graduation rates. Within Oklahoma—given that a majority of counties are rural—the percent of individuals in poverty was significantly associated with violent crime.

Research question 2.2 asked, “Are there identifiable patterns in search engine platforms that preceded criminal violence pertaining to methamphetamines that will aid in community surveillance and prevention?” After completion of analysis, we did not find any evidence that online activity —search queries or social media (Twitter) predicted methamphetamine-related crime. This likely implies that individuals engaged in methamphetamine use are not discussing the activity on Twitter. They are also not searching for items related to methamphetamine on Google. The lack of Twitter searchers could be that Twitter is not the platform of choice for users, instead using other mediums such as Reddit or Facebook.

Discussion

The research is expected to be utilized by communities and stakeholders to have a better understanding of the drivers of negative outcomes in their communities. By establishing the procedures to monitor based on past data, future data can be predicted. More closely monitoring of SDOH and ACEs in a community can help determine to what degree methamphetamine use and violence will be affected. Further, providing a metric to all corners of this spider web, stakeholders from different areas can work together to better combat negative outcomes at the community level.

A project of this size and scope is bound to have limitations. Since this project utilized large data sets most of the limitations are in the data itself. The limitations of each data set should be discussed independently.

The first limitation involves the use of methamphetamine overdoses as a metric for methamphetamine use within a community. This hypothesis utilizes a “tip of the iceberg” concept, in which overdoses are a rarer event that speak to the prevalence of events underneath (methamphetamine use). Historically, this assumption was more accurate (*Meth Overdose Deaths Surge*, 2021). However, recent trends in methamphetamine use include combining this substance with illicitly manufactured fentanyl (IMF), leading to more deaths (*Meth Overdose Deaths Surge*, 2021; Seaman et al., 2022). Therefore, more overdoses may not necessarily represent more use in a community, but instead, more lethality in user behavior. The other limitation in utilizing methamphetamine overdoses has already been alluded to: suppression. The fact that counties with suppressed data is not trivial (83% in WONDER and 45% within County Health Rankings). This limitation was mitigated against by the use of MICE (Multiple Imputation with Chained Equations). To adequately address this limitation, unsuppressed data has been requested from the CDC.

The other metric for methamphetamine use in a community was methamphetamine specific crimes. This also has limitations. It requires the individual to be charged, and for that charge to be reported either to UCR/NIBRS or OSCN. Further, it represents a charge and not a conviction. This last point should have minimal impact for comparison purposes as it should be equally inaccurate among all jurisdictions. However, certain geographic regions have more ability to intersect methamphetamine users and distributors. For example, if a county has an interstate or interstates transecting it, it is likely to have more attention from law enforcement and therefore have more charges.

As discussed above, NIJ-defined violent crimes were categorized into Goldstien's Drugs/Violence Nexus as psychopharmacologic, economic-compulsive, and systemic violence. The categorization by the project team was based on the opinion/experience of project investigators. Future analysis, including an interrater reliability (IRR) study, should be performed to remove bias/subjectivity from this classification. Further, these categories can overlap. It is certainly possible to murder an individual while psychotic and intoxicated on methamphetamine, representing psychopharmacologic violence. It is also possible to murder a rival drug dealer for control of territory. However, in our analysis, murder was solely assigned as "systemic" violence. Future studies should involve analysis of cases for each of the crimes, combined with IRR to improve the accuracy of this classification.

Project Notes

The project was led by a team of three investigators: Jason Beaman D.O., Micah Hartwell Ph.D, and Ron Thrasher Ph.D. All three are faculty at Oklahoma State University Center for Health Sciences located in Tulsa, Oklahoma. Drs. Beaman and Hartwell are faculty in the Department of Psychiatry and Behavioral Sciences. Dr. Thrasher was a faculty member of the School of Forensic Sciences. Dr. Thrasher retired in June 2022. Since his retirement was towards the end of the grant period, it was decided not to replace this position. Dr. Thrasher's expertise in drug courts and Indian Country was valuable in the early stages of the project. We do not believe his retirement had a negative impact on the project. Additionally, the project was supported by the work and contributions of project staff. Project staff included a Research Assistant, Data Analyst, and two Graduate Research Assistants.

The project has not yet collaborated with other entities outside of Oklahoma State University. However, as the research and outcomes become disseminated, we anticipate opportunities to work with other experts including law enforcement, legislators, and academia, to further expand knowledge in this field.

The planned structural equation model was changed to a path analysis due to the variable of high school graduation rate, poverty (%), and unemployment rate at the community level not having a good fit within a confirmatory factor analysis, thus not allowing it to be considered a latent construct at the county level. Ergo, we opted to use unemployment rate as a measured variable in a path analysis (as a proxy variable for low SES).

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