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RESEARCH ARTICLE

Social vulnerability predictors of drug poisoning mortality: A machine learning analysis in the United States

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Abstract

Background and Objectives: Drug poisoning is a leading cause of unintentional deaths in the United States. Despite the growing literature, there are a few recent analyses of a wide range of community-level social vulnerability features contributing to drug poisoning mortality. Current studies on this topic face three limitations: often studying a limited subset of vulnerability features, focusing on small sample sizes, or solely including local data. To address this gap, we conducted a national-level analysis to study the impacts of several social vulnerability features in predicting drug mortality rates in the United States.

Methods: We used machine learning to investigate the role of 16 social vulnerability features in predicting drug mortality rates for US counties in 2014, 2016, and 2018—the most recent available data. We estimated each vulnerability feature's gain relative contribution in predicting drug poisoning mortality.

Results: Among all social vulnerability features, the percentage of non-institutionalized persons with a disability is the most influential predictor, with a gain relative contribution of 18.6%, followed by population density and the percentage of minority residents (13.3% and 13%, respectively). Percentages of households with no available vehicles, mobile homes, and persons without a high school diploma are the following features with gain relative contributions of 6.3%, 5.8%, and 5.1%, respectively.

Conclusion and Scientific Significance: We identified social vulnerability features that are most predictive of drug poisoning mortality. Public health interventions and policies targeting vulnerable communities may increase the resilience of these communities and mitigate the overdose death and drug misuse crisis.

INTRODUCTION

Accounting for nearly 70,000 deaths annually, drug poisoning, defined as deaths from drug misuse such as overdose or consumption of the incorrect drug, is a leading cause of unintentional deaths in the United States.[1] Much of this increase has been associated with opioid use, with two-thirds of drug overdose deaths being attributed to opioids in 2018, and 70% of drug overdose deaths being attributed to opioids in 2019.[2] The US opioid epidemic can be characterized by three successive opioid-related mortality waves. The first wave (1999–2010) was driven by prescription opioids, the second wave was driven by heroin (2011–2013), and the third wave

(2014–present) has been driven by synthetic opioids (e.g., fentanyl and fentanyl analogs). Currently, the epidemic is evolving with a rising increase of deaths due to opioids mixed with stimulants as well as stimulant-related deaths.[3] Opioid-related complications during the COVID-19 pandemic increased, resulting in higher rates of opioid overdose-related emergency department (ED) visits.[4] Also, fatal drug overdoses disproportionately increased among structurally marginalized populations and minorities amid the COVID-19 pandemic.[5–9]

Overall, drug poisoning has taken a heavy toll on every sociodemographic group in the United States; however, vulnerable populations have been most heavily impacted.[10] The COVID-19 pandemic has further exacerbated this toll by imposing additional social, economic, and health-related hardships, negatively affecting the millions of vulnerable and marginalized people with opioid use disorder. In addition to difficulties stemming from potential disruptions to the global supply of drugs, as drug and treatment acquisition often requires person-to-person contact that breaches social distancing measures, people who use drugs (PWUD) have found themselves facing limited access to healthcare services such as naloxone or medications for opioid use disorder.[11] As the COVID-19 pandemic continues to affect vulnerable populations,[12] analyzing and understanding the impacts of a wide range of community-level social vulnerability features on drug poisoning at the national level is more critical now than ever.

Prior studies have attempted to address the drug poisoning epidemic by analyzing its association with various social vulnerability features ranging from ethnicity and age to employment and opioid supply. For instance, research suggested that the likelihood of drug use disorder and poisoning is correlated with an individual's socioeconomic status, including poverty as well as geographic location.[13,14] A recent study found that social capital and workforce participation accounts for between-state variation in poisoning deaths in non-Hispanic Whites.[13] A study in Tennessee found that from 2013 to 2016, fentanyl and heroin overdoses were higher among younger age groups, non-Hispanic Blacks, and people with education greater than high school.[15]

Additionally, a recent study explored the demographic and drug patterns in overdose deaths among US Hispanics and reported a substantial variation in Hispanic drug overdose mortality rates for each subgroup (i.e., non-Hispanic Whites and Puerto Rican-heritage Hispanics).[16]

Another study found that drug-related mortality rates are higher in counties with family and economic distress and are lower in counties with higher religious activities.[17] Overall, economic distress, especially in rural counties, is a strong predictor of drug mortality rates,[18] and economically disadvantaged counties experience more prescription opioid overdoses.[19] Additionally, the economically vulnerable populations are at risk by the supply of opioids.[17] This means that high dispensing rates of prescription drugs, higher social vulnerability, and economic distress work as a fire-triangle and are key drivers of the prescription drug epidemic and drug poisoning mortality.

The scientific literature has seen a growing number of studies analyzing different vulnerability features and reported an association between these features and drug overdoses.[13,17,18,20] However, these reports face three major limitations: often studying a limited subset of vulnerability features, focusing on small sample sizes, or solely including local data. For example, a recent study that analyzed the impacts of several vulnerability features at the national level was based on the 2010–14 American Community Survey, which lacked data for more than half of the counties.[20] Another study examined the relationships between economic opportunity and the prevalence of prescription opioids and substance use in the United States and reported that counties with lower economic opportunity are more likely to have higher rates of opioid prescriptions, opioid-related hospitalizations, and drug overdose deaths.[21] Also, geospatial and statistical analyses showed regional imbalances between access to treatment for opioid use disorder and opioid mortality.[22] Further research investigated the role of the geographical aspects of drug-related death in the United States and focused on intranational contextual variation.[23] Additionally, using novel machine learning approaches with a stronger predictive power can provide more accurate and robust results.[24–27]

To address this research gap, we used the most recent and complete data reported in the Social Vulnerability Index, developed by the Centers for Disease Control and Prevention (CDC) to aid emergency response planners and officials in identifying at-risk communities during public health emergencies.[28] Social vulnerability refers to the resilience of communities against external stresses on human health and economic loss caused by natural or human-made disasters or disease outbreaks. Communities with higher social vulnerability rates experience higher human suffering and economic loss. The CDC's social vulnerability features (index) consist of four broad domains: socioeconomic status, household composition and disability, minority status and language, and housing type and transportation.[29] Using social vulnerability features and data on drug poisoning, we conducted a machine-learning analysis to determine the specific community-level vulnerabilities that are most predictive of drug poisoning mortality rates.

METHODS

This study included 16 social vulnerability features and drug poisoning mortality rates for 3127 counties in the United States. Fifteen of the social vulnerability features were provided by the most recent and complete data available, found from 2014, 2016, and 2018 iterations of the CDC's Social Vulnerability Index (see Table 1).[29] Population density per square mile, as provided by the CDC separately,[23] was included as the sixteenth feature in the analysis.[24]

Drug mortality data for the respective years were collected from the National Vital Statistics System,[30] where drug poisoning mortality was defined as having drug poisoning as an underlying cause of death (i.e., the disease or injury which initiated the train of events leading directly to death, or the circumstances of the accident or violence which produced the fatal injury," and defined by the World Health

TABLE 1 Definition of social vulnerability features.

Domain	Feature	Definition
Socioeconomic Status	Below poverty %	Percentage of persons below federal poverty level
	Unemployment rate %	Number of persons who are unemployed but seeking a job
	Per capita income	Per capita annual income in dollars
	No high school diploma %	Percentage of persons with no high school diploma (age 25+)
Household Composition and Disability	Age 65 and older %	Percentage of persons aged 65 and older
	Age 17 and younger %	Percentage of persons aged 17 and younger
	Noninstitutionalized with a disability %	Percentage of civilian noninstitutionalized population with a disability
	Single-parent households with children %	Percentage of single-parent households with children under 18
Minority Status and Language	Minority (except white, non-Hispanic) %	Percentage minority (all persons except White, non-Hispanic)
	Age 5+ who speak limited English %	Percentage of persons (age 5+) who speak English "less than well" estimate
Housing Type and Transportation	Housing in structures with 10+ units %	Percentage of housing structures with 10 or more units out of all residential housing types
	Mobile homes %	Percentage of mobile homes out of all residential housing types
	Over occupied housing units %	Percentage of occupied housing units with more occupants than number of rooms
	Households with no vehicle available %	Percentage of households with no vehicle ownership
	Institutionalized group quarters %	Percentage of persons residing in institutionalized group quarters (e.g., correctional institutions, nursing homes)
Population density	Population density per square mile	Number of persons per square mile

Note: For the comprehensive definitions of the SVI variables and methodology, see CDC SVI 2018 Documentation: https://svi.cdc.gov/Documents/Data/2018_SVI_Data/SVI2018Documentation.pdf.

Organization [WHO]),[31] based on ICD-10 clinical classification codes (unintentional [X40-X44], suicide [X60-X64], homicide [X85], or undetermined intent [Y10-Y14]).[32] All data were collected from publicly available sources.

We used extreme gradient boosting (XGBoost) to model drug poisoning mortality rates based on each county's social vulnerability features. As a common supervised learning, nonparametric, and tree-based classification approach, this method is especially suitable to analyze all potential features together, considering possible non-linearities, spatial autocorrelation, and multicollinearities among the features.[25,26] Specifically, the XGBoost model is superior to traditional regression models; it avoids multicollinearity problems, has stronger predictive power, and accommodates outliers and missing values. Also, these models do not generate *p*-values and therefore do not predetermine the association between predictor and predicted variables.[24,27] We report gain to interpret prediction results. Gain denotes each feature's relative contribution in explaining variation in the dependent variable (i.e., drug poisoning mortality rates). A higher feature gain compared to other features implies greater importance of the feature for generating a prediction.[33,34] Gain is a metric used to train Decision Trees. Decision Trees create a training model to predict the value of the target variable (i.e., drug poisoning mortality rates) by learning simple decision rules inferred training data set. In practice, one level of the tree would be optimized at a time. Specifically, the software split a leaf into two leaves. Gain measures a split's quality to determine how much information a feature provides. In the Decision Tree training process, the best split is chosen by maximizing gain.[35]

Our training data set contained a random subset of 2502 counties (80% of the total 3127 counties), and our testing data set consisted of the remaining 625 counties (20%). The all-year analysis included data for 2014, 2016, and 2018 with the number of counties for each year. Therefore, a random subset of 7505 counties (80% of the total 9831 counties), and the testing data set consisted of the remaining 1876 counties (20%).

To check for overfitting or selection bias, especially with regard to spatial autocorrelation,[36] we applied a 10-fold cross-validation to tune the model's hyperparameters and assess the generalizability of the results. Additionally, we conducted sensitivity analyses by adding the opioid dispensing rates (a potential confounding variable),[37] as another independent variable to the 16 social vulnerability features. We also conducted additional linear regression and linear regression with multiple interactions and compared the robustness of the machine-learning model compared to the traditional regression model. We used RStudio 4.0.2 (R Core Team, 2020). No human subjects were involved in this study, hence no research ethics approval was needed.

RESULTS

Supporting Information: Figure SA1 presents county-level drug poisoning mortality rates per 100,000 people. The highest rates are clustered in the Appalachian region and the Northeast, followed by parts in the South and West of the United States. Drug poisoning mortality rate ranged from three to 107 per 100 K people.

Table 2 also provides sample characteristics of the social vulnerability features and drug poisoning mortality rates per 100,000 people.

The evaluation metrics results and the goodness of fit in the 10-fold assessment (adjusted $R^2 = 0.67$, MAE = 3.19, and RMSE = 4.52) summarize the observed discrepancy between the predicted mortality rates and the actual mortality rates (Supporting Information: Table SA1). The goodness of fit and prediction evaluation for linear regression and linear regression with multiple interactions were not as robust as the machine learning model (see Supporting Information: Tables SA4–A6).

TABLE 2 Descriptive statistics of the social vulnerability features and drug poisoning mortality rates per 100,000 people in 3127 counties in the United States (2014, 2016, 2018).

Social vulnerability feature	Min	Mean	Max	Std. dev
Below poverty %	1	16.3	55.1	6.5
Unemployment rate %	0	7	29.9	3.5
Per capita income	8200	25,363	72,832	6189
No high school diploma %	1.2	14.2	66.3	6.6
Aged 65 and older %	3.3	17.6	55.6	4.5
Aged 17 and younger %	1.1	22.6	40.3	3.5
Noninstitutionalized with a disability %	3.8	15.8	37	4.4
Single-parent households with children %	0	9	25.6	2.7
Minority (except white, non-Hispanic) %	0	23	99.3	20
Age 5+ who speak limited English %	0	2	32.7	2.9
Housing in structures with 10+ units %	0	5	89.8	5.6
Mobile homes %	0	13	63.1	9.5
Over occupied housing units %	0	2	38.9	2.2
Households with no vehicle available %	0	6	78	4.3
Institutionalized group quarters %	0	4	59.3	4.6
Population density per square mile	0.04	268	72,168	1795
Drug poisoning mortality rate per 100 K people	3	19	107	8

Figure 1 presents the results of our machine learning analysis, the gain relative importance of each social vulnerability feature, for all years as well as each separate year. The percentage of non-institutionalized persons with a disability is the most important feature in predicting drug poisoning mortality, followed by population density per square mile and percentage of minority (all persons other than White, non-Hispanic) residents. The relative predictive contributions (gain) of these three features are 18.6%, 13.3%, and 13.0%, respectively.

The other features have much smaller gain relative importance: percentage of households with no vehicle available, percentage of mobile homes, and percentage of persons with no high school diploma have relative predictive contributions of 6.3%, 5.8%, and 5.1%, respectively. The rest of the features each had a gain relative importance of less than 5%. The three features that were least predictive of drug poisoning mortality rates included the percentage of institutionalized group quarters, the percentage of over-occupied housing units, and the percentage of single-parent households with children (also see Table 3).

We repeated the analysis by adding opioid dispensing rates to assess its impact as a potential confounding variable. Results were substantively the same as the results for all-year data combined, building confidence in our primary analysis. The percentage of noninstitutionalized persons with a disability, with a relative gain of 20.7%, remains the most important feature in predicting drug poisoning mortality, followed by population density per square mile with a relative gain of 13.8%, and percentage of minority (all persons other than White, non-Hispanic) residents with a relative gain of 12.6%. The percentage of opioid dispensing rate had a relative gain of 3.5%.

DISCUSSION

This study examined the association between drug poisoning mortality and social vulnerability features across counties in the United States. Results demonstrated that the most predictive vulnerability features of drug poisoning mortality include the percentage of residents with disability, population density, minority status, followed by the percentage of households with no vehicle available, mobile homes, and no high school diploma. The sensitivity analysis results were similar when we added opioid dispensing rates as a potential confounding variable (see Supporting Information: Tables SA2 and SA3).

The percentage of noninstitutionalized residents with a disability is the most important predictor of drug poisoning mortality. This percentage may be due to the high rates of opioid analgesic prescriptions within this population[38] or low utilization of opioid

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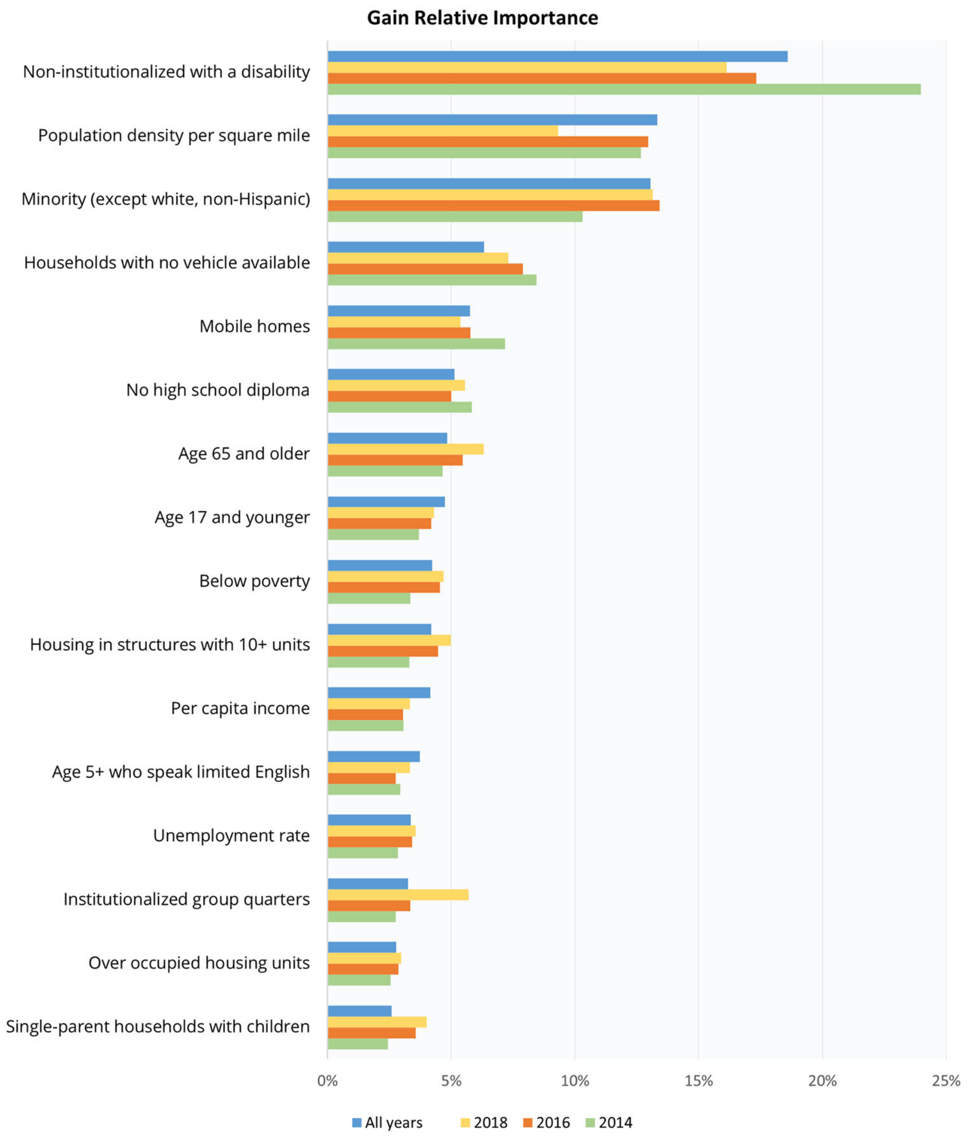

FIGURE 1 Gain relative importance gain is used to interpreting prediction results, denoting each feature's relative contribution in explaining variation in outcomes (i.e., drug poisoning mortality). A higher feature gain implies greater importance of the feature for generating a prediction.

use disorder treatment,[39] among other features. In the same way, Medicare beneficiaries with disability make up nearly 15% of the Medicare enrollees and account for more than 80% of Medicare enrollees' opioid overdose deaths.[40]

Although the importance of this feature (the percentage of noninstitutionalized residents with a disability) declines between 2014 and 2018 and supports the replacement of prescription opioids with street and illicitly manufactured drugs (e.g., heroin and fentanyl),[41,42] the results should be interpreted with caution. The Americans with Disabilities Act (ADA) includes people with addiction to alcohol and people in recovery from opioid and substance use disorders in people with disabilities.[43] This may cause overestimation of the disabilities variable overall gain score. Therefore, analyzing the underlying causes is subject to further analysis. Targeted interventions and policies may be needed to mitigate the risk of drug poisoning mortality for disabled individuals.

Population density follows as the second most predictive feature in predicting drug poisoning mortality, corroborating prior research on the importance of location and population density. This means counties with higher population density would experience higher drug poisoning mortality rates. Studies have shown that from 1999 to 2017, age-adjusted drug overdose death rates in urban counties increased by 344%; in comparison, the rates increased by 500% in rural counties.[44] In particular, there is a notably large concentration of high drug overdose deaths in rural Appalachia. Furthermore, drug overdose death rates are significantly different among neighborhoods within rural or urban areas, varying up to 13-fold,[45] adding to the importance of population density in drug poisoning mortality rates. Also, the relative gain of other features (i.e., housing in structures with 10+ units, households with no vehicle available, and the number of mobile homes) stresses the impact of neighborhoods on drug overdoses.

TABLE 3 Feature importance matrix for the social vulnerability features, all years.

Social vulnerability feature	Gain (%)	Cover (%)	Frequency (%)
Noninstitutionalized with a disability %	18.54	8.23	6.62
Population density per square mile	13.32	14.53	9.80
Minority (except white, non-Hispanic) %	13.05	8.35	7.96
Households with no vehicle available %	6.33	5.99	6.02
Mobile homes %	5.75	6.84	6.74
No high school diploma %	5.13	5.44	6.40
Aged 65 and older %	4.83	4.86	5.93
Aged 17 and younger %	4.75	4.87	5.41
Below poverty %	4.23	5.44	6.09
Housing in structures with 10+ units %	4.20	5.04	5.60
Per capita income	4.15	9.38	7.70
Age 5+ who speak limited English %	3.73	3.08	4.33
Unemployment rate %	3.37	5.13	6.11
Institutionalized group quarters %	3.25	4.22	5.28
Over occupied housing units %	2.78	3.68	4.73
Single-parent households with children %	2.59	4.92	5.28
Sum %	100	100	100

Note: XGBoost uses different importance metrics, including gain, cover, and frequency of features. Gain denotes the relative contribution of a feature in the model (i.e., a higher feature gain implies higher importance for generating the prediction). Cover indicates the average coverage of splits that use a specific feature. It corresponds to the percentage of the used observations of feature to decide the leaf node for them. Frequency represents the relative number of times a particular feature occurs across all the trees estimated within the model.

For example, mobile homes are primarily occupied by people with lower socioeconomic status.[46,47]

The third most important predictor of drug poisoning mortality is the percentage of minority populations. This means counties with a higher percentage of minority would experience higher drug poisoning mortality rates. Though the opioid epidemic has primarily impacted non-Hispanic whites, the opioid overdose death rate among African Americans has accelerated and is currently outpacing that of whites, leading to a growing race/ethnic disparity in recent years.[48,49] Finally, we found that among the studied social vulnerability features, single-parent household was the least predictive feature of drug poisoning mortality, contesting prior research.[20]

Accounting for large increases in unemployment rates and economic and housing insecurity among low-income and minority individuals stemming from the COVID-19 pandemic,[50,51] our findings highlight the need to monitor and address future increases in drug poisoning deaths as a further consequence of the pandemic, particularly in counties with large minority populations. Improving social structures related to these vulnerability features (e.g., education, income, housing disparities) through measures such as intervention and policy for vulnerable communities may increase the resilience of these communities and mitigate the overdose death and drug poisoning crisis.

Our study extends prior research methods on this subject, particularly regression-based analyses, by using a machine learning approach and more recent and complete data. As discussed earlier, our approach provides more accurate and robust results because it takes into account the complexity of the data (e.g., nonlinearities and multicollinearities) and is not prone to biases related to data imputation in regression-based methods. However, this study should nevertheless be interpreted in the context of certain limitations: our results do not establish causality. Also, drug poisoning mortality rates in a few counties were reported to be 0. This could be due to data availability or low mortality rates per 100,000 people. In addition, other features that may have a crucial role in drug use and mortality, like healthcare and policy environments, are subject to future investigations. While this study focuses on the impact of social vulnerability on drug-related deaths, there are other contextual factors (e.g., emergency response systems speed, access to naloxone, etc.) that may affect drug-related deaths in a county. Also, unlike COVID-19 data, drug poisoning mortality data are reported with several years of lag. Recent studies have reported increased drug overdoses among minorities and marginalized populations during the COVID-19 pandemic.[5–9] Thus, with the availability of more recent data, our analysis can be updated to study the impacts of COVID-19 on our findings. Moreover, with data from additional years, researchers can investigate whether different social vulnerability features have differential associations at different points in time. Future research can also focus on analyzing the heterogeneity of the pattern of each vulnerability feature across communities.

AUTHOR CONTRIBUTIONS

All authors made a significant contribution to the work reported, whether that is in the conception, evaluation design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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