Using Internet search terms to forecast opioid-related deaths in Connecticut

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Background. The opioid crisis has generated substantial social and economic burdens on the United States. Given recent increases in opioid-related fatalities associated with synthetic opioids and evidence that opioid-related deaths cluster geographically, predictive modeling of opioid-related fatality outbreaks could facilitate early interventions during periods of higher mortality risk. Others found associations between national rates of social media posting about synthetic opioids and related deaths and state-level estimates of opioid prescription misuse and tweets that mentioned such misuse. We sought to determine whether internet searches for opioid-related terms were predictive for opioid-related fatality spikes in the following week.

Methods. We conducted a retrospective, observational study seeking to predict opioid-related fatality spikes in one week from the frequency of Google search terms in the previous week in Connecticut between 2012-2018. We obtained search trends corresponding to drug names and related search terms; created separate but overlapping list of search terms corresponding to opioid-, non-opioid-, and withdrawal-related searches; and created a time series that aggregated weekly numbers of those search terms. From a publicly available, de-identified, time- and location-stamped dataset of drug-related fatalities in Connecticut between 2012-18), we calculated a time series of weekly opioid-related fatalities, classified by the drugs found during autopsy into: synthetic opioids (Fentanyl); illicit opioids (heroin); prescription opioids (e.g., Percocet or methadone); and any of the aforementioned in aggregate. We defined an opioid-related fatality 'spike' as a 1 standard deviation increase in the numbers of such deaths, week-to-week. We used logistic regression to predict an overall or categorical opioid-related fatality spike in one week (in an out-of-sample manner) from search trends in the previous week. We calculated the area under the curve (AUC) for an auto-regressive model and 5 predictive models that included the following search terms: randomly chosen English words; non-opioid-related substances with abuse potential; withdrawal-related; overall and categorical opioid-related; and both withdrawal- and opioid-related. For both deaths and search terms, long-term and seasonal trends were removed through a difference transformation; stationarity was verified with an Augmented Dickey-Fuller test (p-value < 0.05). All data are publicly available; therefore, human subjects review was not required.

Results. Models predicting a spike in the number of opioid-related fatalities in the following week that combined opioid-related and withdrawal search terms had the highest AUCs (ranging from 0.863 (for synthetic opioids) to 0.822 (for prescription opioids)). When used alone, categorical opioid-related search terms and withdrawal search terms had AUCs between 0.659 and 0.829. Models using auto-regression, random search terms, and search terms for other substances with abuse potential demonstrated relatively low AUCs (ranging from 0.647 to 0.765). Models that included withdrawal search terms and categorical opioid-related search terms had the highest predictive accuracy, bettering models with withdrawal search terms alone; the synthetic opioids model had the lowest false positive rate.

Conclusion. Models that used volumes of search terms for opioids and withdrawal related terms to predict a spike in opioid-related fatalities in Connecticut between 2012-2018 had high predictive capacity; those using search terms combining synthetic opioids and withdrawal performed best. While our analysis is limited by its restriction to one state, its reliance on search terms from 2012-2018, and the inability to conduct more granular geographic analyses, it suggests that, in concert with surveillance of social media postings, monitoring the frequency of opioid-related and withdrawal search term trends might help communities anticipate periods of high community risk for opioid-related fatalities and intervene to reduce that risk. While further study is required to validate our findings, access to granular data covering larger geographic settings would facilitate such efforts.