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Invited Commentary

Invited commentary: motivating better methods—and better data collection—for measuring the prevalence of drug misuse

Mathew V. Kiang*[,1] and Monica J. Alexander[2,3]

[1]Department of Epidemiology and Population Health, School of Medicine, Stanford University, Palo Alto, CA 94304, United States
[2]Department of Sociology, Faculty of Arts and Science, University of Toronto, Toronto, ON M5G 1Z5, Canada
[3]Department of Statistical Sciences, Faculty of Arts and Science, University of Toronto, Toronto, ON M5G 1X6, Canada
*Corresponding author: Mathew V. Kiang, Department of Epidemiology and Population Health, Stanford University School of Medicine, 1701 Page Mill Road, MC: 5560, Palo Alto, CA 94304 (mkiang@stanford.edu)

Abstract

The United States continues to suffer a drug overdose crisis that has resulted in over 100 000 deaths annually since 2021. Despite decades of attention, estimates of the prevalence of drug use at the spatiotemporal resolutions necessary for resource allocation and intervention evaluation are lacking. Current approaches for measuring the prevalence of drug use, such as population surveys, capture–recapture, and multiplier methods, have significant limitations. In a recent article, Santaella-Tenorio et al (*Am J Epidemiol*. 2024;193(7):959-967) used a novel joint bayesian spatiotemporal modeling approach to estimate the county-level prevalence of opioid misuse in New York State from 2007 to 2018 and identify significant intrastate variation. By leveraging 5 data sources and simultaneously modeling different opioid-related outcomes—such as numbers of deaths, emergency department visits, and treatment visits—they obtained policy-relevant insights into the prevalence of opioid misuse and opioid-related outcomes at high spatiotemporal resolutions. The study provides future researchers with a sophisticated modeling approach that will allow them to incorporate multiple data sources in a rigorous statistical framework. The limitations of the study reflect the constraints of the broader field and underscore the importance of enhancing current surveillance with better, newer, and more timely data that are both standardized and easily accessible to inform public health policies and interventions.

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Key words: opioids; drug misuse; prevalence; bayesian modeling.

Editor's note: *The opinions expressed in this article are those of the authors and do not necessarily reflect the views of the* American Journal of Epidemiology. *A response to this commentary appears on page 17.*

Introduction

Despite decades of significant attention, the United States continues to suffer a devastating drug overdose crisis that has resulted in over 100 000 deaths annually since 2021.[1] Opioids, especially illicitly manufactured synthetic opioids, remain the prominent driver of drug-related deaths,[2] with significant variation in mortality across time, geography, and sociodemographic groups.[3-8] Opioid overdose deaths are a tragic result of the broader issue of opioid misuse and addiction in the United States. Building health-care systems[9-11] and social and economic structures[12] tailored to the needs of local communities to address opioid misuse and addiction is essential to addressing the drug overdose crisis, especially among the most vulnerable.[5,13] However, foundational information on the prevalence of opioid misuse—defined as the use of prescription opioids intended for somebody else, the use of prescription opioids for reasons other than why they were prescribed, or the use of illicit opioids—is rarely available at spatiotemporal resolutions that are programmatically relevant for allocating resources, prioritizing interventions, or assessing intervention effectiveness. In an important study recently published in the *Journal*, Santaella-Tenorio et al[14] used a joint bayesian spatiotemporal model to estimate the county-level prevalence of people who misuse opioids in New York State. In doing so, the authors offered an example of how to integrate multiple data sources and jointly model multiple outcomes simultaneously to estimate the size of hidden populations in a statistical framework.

Counting who counts

Timely, accurate estimates of the prevalence of medical conditions are critical to ensuring that a public health system is equitable and responsive. Such information is necessary for efficiently allocating resources and funding and for monitoring the levels and trends of specific health outcomes. Equitable resource allocation and responses are especially salient in the context of addressing drug misuse given the shortage of treatment professionals[15] and the well-documented disparities in health-care access, treatment, and health outcomes.[7,8,16-19] Surveillance at high spatial and temporal resolutions is essential, as both the substances distributed in the illicit drug market and their potency

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are continuously evolving. Prevalence estimates are also important for assessing the impact of public health interventions, prioritizing interventions, and ensuring equity in access to care and interventions. Despite this critical need, there is a lack of reliable estimates of the prevalence of opioid misuse in the United States.

Population-level surveys are the primary tool for prevalence estimation; however, they have long been recognized to be inadequate for quantifying drug use, for a variety of reasons.[20] First, because drug use is relatively rare, surveys must be large for researchers to obtain reliable estimates. Second, surveys often use households as the sampling frame, making individuals experiencing housing instability less likely to be included and excluding individuals in correctional or treatment facilities, which significantly biases estimates downward given the prevalence of these conditions among people who use drugs. Underestimation may still be an issue even when people who use drugs are included in a survey because drug misuse is stigmatized (and often illegal) and thus people who use drugs may be less inclined to self-report accurately.[21] Other survey methods, such as respondent-driven sampling[22] and network scaling,[23] may address some validity and reliability concerns but are often logistically difficult to scale beyond their target area and to use to capture information repeatedly over time.[21]

Rather than directly estimating the prevalence of drug use through surveys, researchers are increasingly employing indirect estimation methods, which address many of the weaknesses of survey-based methods by leveraging existing data related to the outcome of interest. The two most popular methods are capture–recapture and multiplier methods.[21,24,25] Capture–recapture methods leverage multiple, linkable data sources to gain information on how often a person who uses drugs appears in both (or all) data sources. One can infer the size of the target population if a number of assumptions are met: namely, that the data sources are independent, homogeneous, and representative and that there is no misclassification. Capture–recapture methods have several limitations, and the methods require accurate linking of individuals across datasets—a particular challenge in drug use research.[24,26,27] Multiplier methods are special cases of capture–recapture methods that can leverage but do not require the linking of individuals across datasets. Instead, multiplier methods use an estimate of the proportion of people in a subgroup (ie, a multiplier), such as the fraction of people who use opioids who attend opioid treatment programs, and a known number, such as the number of people in opioid treatment programs (ie, a benchmark), to calculate overall prevalence.[21] The key assumption here is that the estimate of the multiplier is both representative and unbiased—an assumption that is difficult to validate without data linkage.[27]

Santaella-Tenorio et al[14] overcome many of these limitations by using a sophisticated bayesian modeling approach to estimate the annual county-level prevalence of opioid misuse in New York State from 2007 to 2018. They leverage 4 datasets that each contain different opioid-related outcomes—opioid-related mortality, opioid-related emergency department visits, people receiving buprenorphine, and people receiving methadone—as well as survey-based estimates of statewide prevalence. Assuming that state-level survey estimates are accurate and that each of these outcomes and datasets contain proxy information about people who misuse opioids, the authors model all outcomes simultaneously in a joint bayesian spatiotemporal model to obtain county-level estimates of underlying prevalence with uncertainty. Importantly, this model does not require individuals to be linked across datasets and uses existing routinely collected data, thereby avoiding the logistical hurdles of respondent-driven sampling or other small area survey–based methods.

Methodological innovation leading to policy-relevant insights

Building on previous work estimating the prevalence of opioid misuse in Ohio,[28] Santaella-Tenorio et al[14] use an expanded bayesian approach that yields several important policy-relevant insights and serves as a general framework for future research. They find substantial variation in the prevalence of opioid misuse across both time and geography; for example, in one year, there was a nearly 8-fold difference in the prevalence of opioid misuse across counties.[14] Similarly, while the prevalence of opioid misuse declined across most counties, several counties had (and continue to have) a lower prevalence in 2007 than most counties in 2018. Identifying higher- and lower-risk counties may help inform policy decisions related to resource allocation or intervention prioritization.

Once estimates of the prevalence of opioid misuse are obtained, the framework employed by Santaella-Tenorio et al allows modeling of outcomes as a rate among people who misuse opioids rather than among the total population. This may better reflect the true population at risk and therefore may be a better metric for assessing the impact of policies or interventions. For example, Santaella-Tenorio et al find that the prevalence of opioid misuse has decreased over time while the rate of opioid-related mortality has increased.[14] This conclusion is consistent with work suggesting that the main driver of the rise in overdose deaths is that the illicit drug supply has become more lethal rather than that demand for illicit drugs has increased.[10,29-31] Thus, the authors note that an increase in opioid-related mortality and emergency department visits does not imply an increase in the prevalence of opioid misuse.[14]

Simultaneously modeling the prevalence of opioid misuse and opioid-related outcomes allows policymakers to identify high-risk areas in which to prioritize increased access to treatment. For example, Santaella-Tenorio et al identify several counties with high rates of opioid overdose among people who misuse opioids but low rates of people receiving either buprenorphine or methadone. In a more nuanced example, they find that New York City counties had among the lowest prevalence of opioid misuse in the state and had the highest rate of people receiving methadone among people who misuse opioids. Despite this, New York City counties also had among the lowest rates of people receiving buprenorphine among people who misuse opioids and among the highest rate of opioid-related mortality among people who misuse opioids. Given the higher patient burden of receiving methadone relative to buprenorphine treatment and the documented racial and ethnic inequities in treatment,[16-19,32] it may be worth investigating whether policies designed to expand buprenorphine treatment to high-need New York City neighborhoods would reduce opioid-related mortality and inequity.

The urgent need for better, newer, and more available data

We commend Santaella-Tenorio et al for their use of sophisticated modeling to answer important questions about a pressing public health issue. The combination of joint bayesian modeling with multiple datasets can often pose significant computational and analytical challenges, yet Santaella-Tenorio et al provide an example of how this strategy can also yield important insights. Their paper also provides an example of the many data challenges that researchers, policymakers, and health-care systems face—data accuracy and timeliness, a lack of standardized reporting across or even within datasets, changes to instrumentation within datasets, and the availability of crucial but proprietary data. For example, the authors' model uses state-level estimates of the prevalence of opioid misuse from the National Survey on Drug Use and Health (NSDUH). This decision is motivated by the fact that these data are the best available, and supplemental analyses indicate that the sum of the county-level estimates aligns with that of the NSDUH state-level estimates. However, the NSDUH is known to underestimate opioid misuse[33-35]—a serious limitation that is acknowledged by the authors. Some of this concern is ameliorated by the fact that the county-level estimates are relative risks rather than absolute numbers and can be meaningfully interpreted as such. However, the issue highlights the challenges that researchers face: Even sophisticated models are hampered by data limitations.

Since 1999, over 1 million Americans have died from fatal drug overdoses.[1] The urgent need for better and newer data is clear. Statistical sophistication may provide some insights, but ultimately, the underlying data are simply not designed to elucidate or measure drug use at the necessary spatiotemporal resolutions in near real time, which limits our progress in addressing the opioid overdose crisis.[36] Without "ground truth" data, modeled estimates cannot be validated.

In addition to novel statistical methods, addressing the opioid overdose crisis will require both improvements to and standardization of current data collection efforts and development of new data sources. Improving current data collection has received significant attention with the release of the National Drug Control Strategy report.[37] For example, there has been a push to create a unified system to track nonfatal drug overdoses across the country.[38,39] Development of new data sources has received less attention, but the associated efforts, while fragmented, have shown promise. For example, Europe has successfully used wastewater-based methods to monitor drug use in more than 100 cities over the last decade.[40] This type of data collection is noninvasive, privacy-preserving, and scalable. Sampling of already collected, deidentified biological specimens may provide rapid, low-cost data and allow detection of novel emerging drugs. Although the United States has piloted this approach on individual urine specimens,[41] analyzing pooled urine samples is an underinvestigated method that may be more cost-effective.[42] Correctly implemented, these methods are privacy-preserving yet highly informative; however, they would require a sustained commitment from agencies. Social media,[43,44] internet searches,[45] and analyses of the dark web[46] are also promising avenues for gaining information at low cost and high scalability, but the representativeness and predictive power of these novel data streams warrant further investigation. Importantly, while the National Drug Control Strategy report acknowledges the need to collect these new data, it does not lay the foundations for how to ensure that such data are available, timely, and standardized, nor does it provide suggestions for how to incentivize researchers to ensure that their data follow these guidelines.

Data are a social product—we decide how, who, and what is worth measuring.[47] The need for better data is clear; however, without a set of data standards, common definitions, and well-aligned incentive structures, new data streams will be limited in their scalability and usefulness. As others have noted, data collection is the most time-intensive part of estimating prevalence[21]; we should not let this effort go to waste because of a reliance on ad hoc data structures and definitions.[27]

Conclusion

In their important paper, Santaella-Tenorio et al[14] offer researchers an example of how to integrate multiple data sources in a statistically rigorous framework to provide estimates yielding policy-relevant insights. We are encouraged by the recent development of bayesian methods for answering epidemiologic questions. At the same time, the authors' work highlights the limits of current data collection, availability, and quality for monitoring pressing public health issues. We hope that the development of more sophisticated models continues, but we also believe that decades into this crisis, it is time to emphasize the need for improved collection of standardized and timely high-quality data.

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Conflict of interest

The authors report no conflicts of interest.

Disclaimer

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Data availability

No data were involved in the preparation of this article.

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