Using Big Data to Predict Future Opioid Trajectories in the City of Cincinnati

Murat Ozer

Introduction

According to the Ohio Department of Health, drug overdose deaths have tripled in the state over the past decade (Ohio Department of Health, 2018). Hamilton County, in which City of Cincinnati is located, alone had 2,397 overdose responses (calls for service for overdoses) in 2017 that resulted in 539 overdose deaths. Similar to the state trend, Hamilton County experienced nearly 31 percent more overdose deaths in 2017 compared to the previous year (Hamilton County Coroner's Office, 2018).

Despite the public sensitivity to increased overdose deaths, little is known about the prevention strategies using big data. Effective prevention strategies inherently require prediction of future opioid problems; however, researchers have limited or no access to the different data sources that collectively help researchers uncover the identifiable patterns of opioid abuse (Burke, 2016). Given this context, the current study seeks an answer to the research question of: To what extent can a variety of data sources, from different agencies, be employed to predict future opioid trajectories.

Data Sources of the Study

The current study uses three main data sources. The first dataset is provided by the Cincinnati Police Department and includes various datasets such as reported crimes, suspect and victim data, arrest data, and field interview reports (FIR) from January 1, 2013 to December 31, 2017. The second dataset comes from the Cincinnati Fire Department and shows emergency medical overdose-related responses from January 1, 2015 to current date. The third and last data set comes from the Hamilton County Coroner's office and shows overdose victim names, date of birth, location of overdose death,victim residential address, demographic variables (sex, race, marital status), and cause of death for the year of 2016.

Methodology of The Study

This study will use the different data sources to identify/better understand the patterns of opioid overdose. For this purpose, first, drug overdose victim names will be merged with Cincinnati Police Deapartment's (CPD) database that includes suspect, victim, arrest, and FIR datasets. using this data, we will figure out to what extent overdose victims have criminal records with the police. Second, we will identify friends, friends of friends, friends of friends of friends of those overdose victims using the principles of social network analysis to identifying a co-addiction network. The goal in this second step is to determine whether overdose victims are directly connected to known drug sellers in the city. Third, we will display the concentration of opioid overdose responses, known drug sales locations, and residential addresses of overdose victims to conduct a placed-based analyses to identify the spatial patterns of opioid overdoses. Finally, we will use CPD data to determine to what extent police contacts (through arrests) prior to overdose can be used as a tool to prevent future overdose trajectories.

Illicit Network of Opioid Overdose

The data obtained from the Hamilton County Coroner's office includes all overdose victims from Hamilton County for the year of 2016. The current study; however, has access only to Cincinnati Police Department data not the other 42 law enforcement agencies in Hamilton County. For this reason, we are required to remove overdose victims from the study if they are not the residents of Cincinnati because those individuals will not have access to police reports from outside thecity's geographic boundaries. After removing those cases, the overdose sample size reduced to 153[1].

Given this context, we merged 153 Cincinnati overdose victim names with CPD data and noticed that 48 overdose victims had a record with the police. For the next step, we wanted to see the social network analysis of those 48 overdose victims to identify whether they are connected to the illicit network of the city that controls both drug market and street violence.[2] We assumed that if two or more individuals were arrested together, committed a crime together, were victims of a crime together, or were stopped by the police together for a field interview, those individuals are connected to each other (i.e., friends of each other). Social network analysis revealed that those 48 overdose victims were connected to 24,792 individuals/nodes in the city according to CPD data ranging from January 1, 2013 to December 31, 2016. The number of relationships/edges is 49,993. In other words, each node has about two different edge connections.

Table 1. Source of Relationships for Social Network Analysis

Source of Relationship	First Degree Relationships	Second Degree Relationships	Third Degree Relationships	Total
Arrested together	3025	1472	574	5071
Field Interview Reports	15033	5974	2018	23025
Victimized a person	9022	6272	2888	18182
Victimized together	1696	1568	451	3715
Total	**28776**	**15286**	**5931**	**49993**

Table 1 reveals that 48 overdose victims were directly arrested (first degree relationships) with others 3,025 times. The largest type of relationships are field interview reports which suggests that overdose victims were hanging out at those precise locations in which police stopped them

[1] Not all 153 Cincinnati residents overdosed in the city limits. In this context, number of Cincinnati residents within the city limits is 112.
[2] We conducted social network analysis to see the associates of those 48 overdose victims until the third degree of friendship/co-offending (friends, friends of friends, friends of friends of friends).

for the interview. During this process, there were other individuals present that formed their social network analysis. Second and third degree friendship networks show how their friends continued to form the social network graph. At this step, we wanted to explore the whole social network of 48 overdose victims to understand whether they are linked to known prolific offenders who make money by selling drugs. For this reason, we dropped the relationships/edges if they do not include any drug related crimes. Our sample significantly dropped to 1,742 relationships after this process. In addition to this, we only included individuals to the sample if they are prolific offenders[3] and if they are arrested more than once for drug related crimes.

After this filtering process, the entire sample is reduced to 147 individuals who are prolific offenders and had criminal records for repeatedly selling drugs. Further analyses showed that 32 out of the 147 prolific offenders are gang members, and the remaining majority of prolific offenders are connected to gang members at their first, second, and third degree level of their friendship network. This analysis suggests that only handful of prolific-gang affiliated criminals are responsible for drug market in the City of Cincinnati. The current findings are also aligned with gang literature that posit majority of gangs sell drugs to make money (National Gang Intelligence Center, 2011).

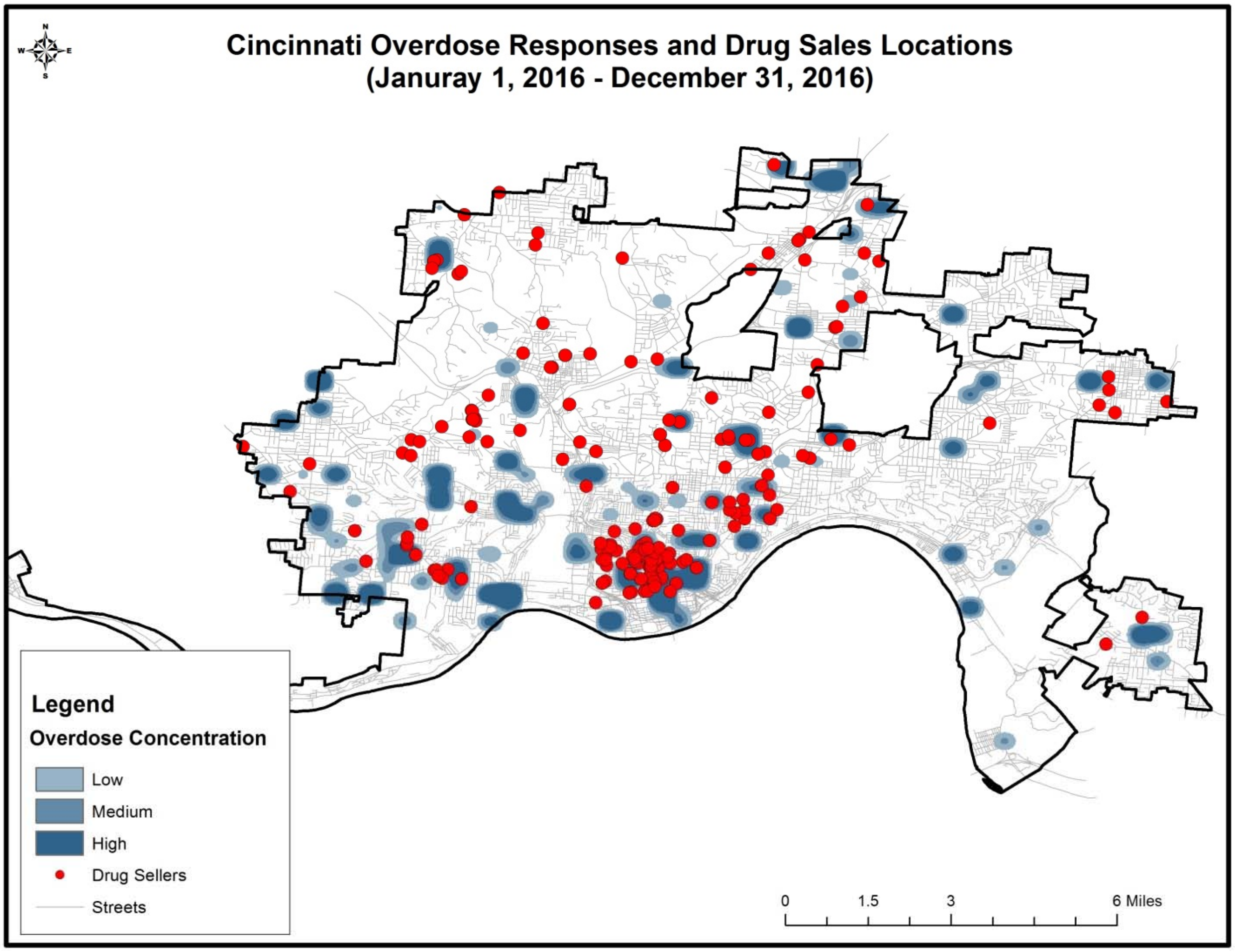
Hot Spot Locations of Drug Overdose Responses

The City of Cincinnati provides the Cincinnati Fire Department's overdose response on the city website[4] from 2015 to the current date. We downloaded the data for the year of 2016 (N=1923). Crime Prevention studies suggest that crime is non-randoly distributed in time and space (Bratingham & Bratingham, 1999; Felson, 2006, Sherman, Gartin, & Buerger, 1989). Based on this notion, we created a kernel density map to show overdose hot spot locations using ArcMap 10.4. In addition to this, we also displayed prolific drug sales locations in order to explore to what extent drug sales locations spatially overlap with overdose responses. As displayed in Figure 1, there is a high correlation between spatial locations of drug sales and the concentration of overdoses. The Southern part of the city has a substantial overlap of overdose victims and drug sales locations. This area alone accounts 30% of overall drug overdoses.

[3] Cincinnati Police Department has been using a special algorithm within the principles of social graph theory to determine prolific offenders. The algorithm strictly follows the core thoughts of criminological theories to prioritize individuals based on their social threat to the community. The current algorithm uses ages to determine early onset individuals for delnqeunt behavior. Past criminal history is another indicator to assess the future violent trjactories of indivuals. Finally, the alogirthm uses social network analysis to include peer influence prediction to the equation. As noted above, the current algorithm assumes that if two persons are arrested, field interviewed, victimized, or committed a crime together they are affiliated and thus categorized as associates. Given this context, the algorithm finds a person's (ego) friends (edges) until a third-degree friendship network, and the entire network is updated every night with the new data inputs . We used this algorithm to identify Cincinnati's prolific offenders.

[4] https://insights.cincinnati-oh.gov/stories/s/Heroin/dm3s-ep3u/

Figure 1. Cincinnati Overdose Responses and Drug Sales Locations



Journey to Overdose

In 2016, there were 121 overdose deaths within the city limits of Cincinnati after excluding the 20 overdose deaths that occurred at the hospital[5]. Of those 141[6], 112 of them were the residents of Cincinnati. We wanted to analyze whether overdose victims made a journey for an overdose, and determine if this journey spatially overlaps with known prolific drug sales offenders. We borrowed the notion of 'journey to crime' from crime prevention literature and applied to opioid overdoses. 'Journey to crime' notion posits that crimes are likely occur closer to offenders' residential places; and the chance of committing crime lowers for an offender as he moves away from his home (Bratingham & Bratigham, 1993; Felson, 2002; Wiles, Paul, & Costello, 2000).

[5] We excluded hospital deaths because it was impossible to determine the original overdose locations for those cases.

[6] Note that this number is different than the above 153 because this number includes all overdose victims that found dead in the Cincinnati city limits.

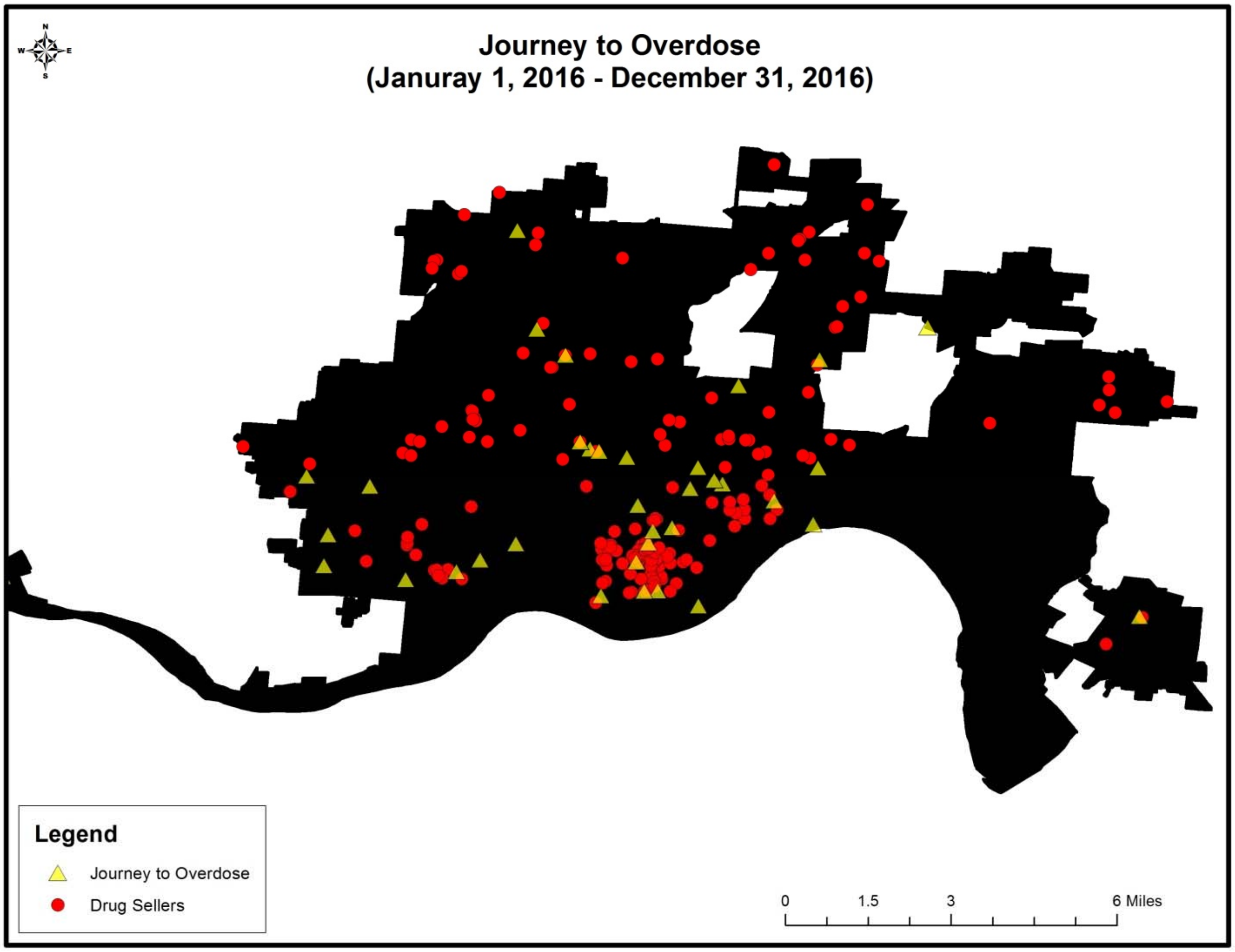
In this context, analysis revealed that 62 of 121 overdose victims (51.2%) overdosed at their place of residence. The remaining overdose victims (N=59) traveled an average of 5.5 miles to overdose. Table 2 reports journey to overdose distances in detail. Further analyses revealed that long distance journeys to known drug sales locations are generally from outsiders/non-residents (N=27). This finding suggests that opposite to Journey to Crime literature, Cincinnati drug sales locations are well known and attract even non-residents from long distances. Considering the resident and non-resident distinction, our analysis suggests that city residents (n=22) travel at average 1.53 miles, and non-residents (n=27) travel at average 8.87 miles to overdose.

Table 2. Journey to Overdose

Distance	# of Overdose
0.1 to 1 mile	8
1 to 2 mile	8
2 to 3 mile	10
3 to 4 mile	1
4 to 5 mile	7
5 to 6 miles	4
6 to 10 miles	10
10 to 20 miles	11

Figure 2 below displays the journey to overdose for those 59 victims. As the map suggests, overdose victims generally travelled to the places where prolific drug sales offenders were present. Putting it differently, drug overdose victims journeyed to the known drug selling spots to purchase their drug/opioids and then overdose right after using the purchased drug/opioid.

Figure 2. Journey to Overdose



Police Contacts and Overdose Victims

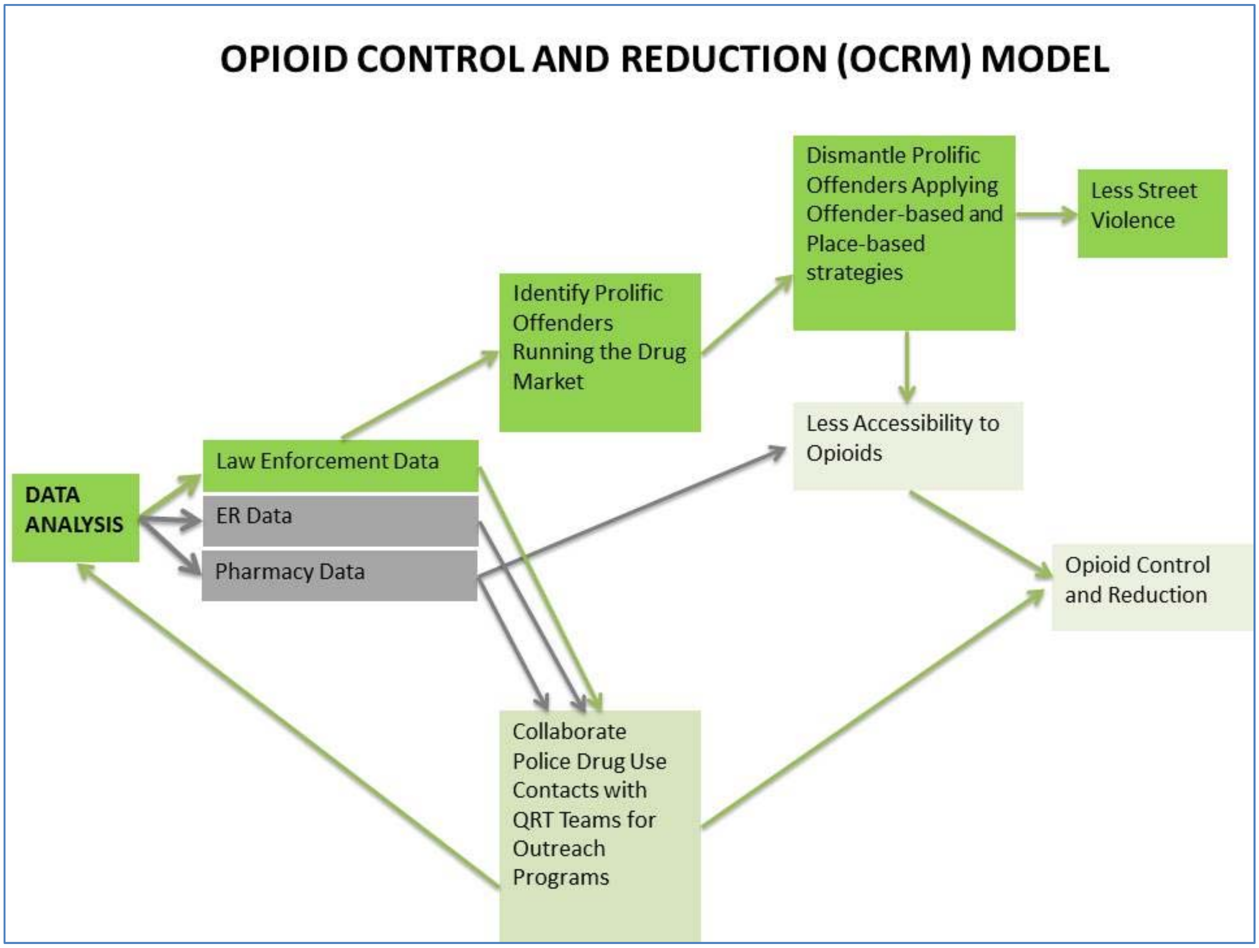
In this section of the study, we aimed to analyze whether police had a prior contact with overdose victims before they overdosed. To determine this, we used 2014, 2015, and 2016 Cincinnati Police Department drug arrest data that included 12,203 drug arrestees[7]. Of those arrestees, we further filtered the data and kept individuals in the sample if they were arrested for only drug usage (i.e., not for drug selling). This filtering process reduced the data to 5,252 for the three year period. At this point, we wanted to see how CPD early police contacts predict future overdose trajectories. For this purpose, we merged Cincinnati overdose victim names with the 5,252 previously arrested individuals and noticed that 12 of 112 Cincinnati overdose victims (10.7%) were previously contacted by the police. This finding suggests that if police contacts can be used in a more proactive way, more lives can be saved.

[7] Unique individual arrestees. Duplicate arrestees, such as those arrested at different times, were dropped from the analysis.

Creating a Proactive Model from The Findings

The current study clearly identifies certain patterns of opioid/drug overdoses which can be used to develop a model to prevent future opioid trajectories. In this context, we offer an Opioid Control and Reduction (OCRM) Model, to control and prevent the opioid/drug epidemic.

Figure 3. Opioid Control and Reduction Model[8]



The first step in the model is the data analysis. Our proposed model requires at least three data sources: law enforcement data, hospital emergency room data, and pharmacy data. However, we currently have only access to law enforcement data in our model which adversely affects the power of the model as discussed below.

The proposed model analyzes law enforcement data to identify small number of prolific offenders that control the drug markets as discussed above. As previous studies found, a majority

[8] Gray colored text boxes suggest that the current study does not have data access for those data sources. For this reason, the likely effects of those missing data sources are also colored with gray arrows due to their unknown status. Darker green text boxes suggest that the current study successfully performs those analyses. If a text box is colored with light green, that means that we need to have more data to perform bettermore detailed analyses.

of gang members and prolific offenders sell illiegal drugs as their primary source of income (Chen, Chung, Xu, Wang, Qin, & Chau, 2004). These same individuals are also the primary sources of street violence. Our analysis also revealed that overdose victims are connected to gang members and prolific offenders that sell drugs. This relationship shows the existence of illicit drug networks that poison drug addicted people and also augments the sreet violence by monetarily securing prolific offenders' positions in the co-offending network. Therefore, dismantling this illicit network, using place-based and offender-based policing techniques can reduce overdose deaths by limiting access to opioids and can also reduce street violence by dismantling the illicit drug network.

Eliminating illicit networks; however, may not be adequate to control the spread of opioids in a given jurisdiction. Pharmacy data are needed to identify those persons who abuse the system to gain access to opioids. Given this context, analyzing pharmacy data provides a better opportunity to control the diffusion of opioids in the community.

Our model suggests using police contacts to proactively provide outreach to opioid users and providing them with treatment options. Police are like our nervous system. They are the first agent that detect the anomalies in our society because they are on the streets 24 hours a day, 7 days a week. Our study findings suggest that police contacts can predict at least 10% of overdose victims before they overdose. In the current setting, the best thing the police do is either arrest or give citations to people who use drugs on the street. Our model offers that we need to use the police contacts more proactively and hand over drug abuse contacts/individuals to agencies (e.g., quick response teams) that devote themselves to solve the opioid problems in the community. This approach is highly doable because police usually make five daily arrests for drug abuse[9]. Collaboratively working with Quick Response Teams can help develop a proactive approach to opioid abuse. As Dasgupta, Beletsky, and Cicarone (2018) suggest, cutting access to opioids migh be a simplistic approach because opioid crisis is linked to economic, sociological, and psychological problems. For this reason, the role of Quick Response Teams are crucial in terms of providing services at patient and community level.

The proposed model; however, also requires emergency room (ER) data in order to increase the accuracy of police contacts for opioid users. If emergency room data (for opioid users) can be merged with the law enforcement data, police can better identify those individuals who are in need of a Quick Response Teams' outreach program. For example, if the police have contact with an individual, who has an history of drug abuse based on medical records, ina known drug hot spot area, the proposed model can directly inform the police officers that Quick Response Teams should be immediately notified of this contact. In this way, police early contacts can be turned into more proactive intervention which then help to reduce opioid trajectories.

[9] Based on our experience using Cincinnati Police Department data

Finally the model gives a vital role to Quick Response Teams because they provide outreach to opioid users for treatment options. These Quick Response Teams should collect data from opioid users such as how they started to use opioids, whether their friends use opioids or not, how they acquire the opioids, what kind of opioids they use and so on. Following the data collection, the data should be added to the existing database pool in order to better analyze the current state of the opioid problem through daily updated data analysis.

Conclusion

This study is is one of the first attempts to use a big data pool to create dynamic models for the prediction of future overdose trajectories. Findings suggest that using big data from multiple sources better help us to understand the patterns of drug overdose. The current study currently has only law enforcement data inputs. For this reason, the prediction of future opioid overdose trajectories is limited. To increase the prediction/prevention capacity, different data sources, specifically from medical field, are needed.

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