Prevalence and Attitudes About Illicit and Prescription Drugs on Twitter

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***Abstract*—As with many other health issues, each day Twitter users report information on their experiences with drugs, giving researchers an unique window on attitudes and behaviors about drug misuse and abuse. Using data collected over two different time periods and covering a broad range of substances, including prescribed opioids and illicit drugs, we present statistics about volume, as well as attitudes with respect to distribution (selling/buying) and need. We find that prescription drugs, such as sleeping pills, Xanax, and Adderall, are the top drugs needed in Twitter. Significantly more users are trying to sell illegal hard drugs, such as heroin and cocaine, rather than buy or claim need for these drugs. Finally, the Twitter chatter related to specific drugs is directly impacted by high-visibility media events involving such substances. Evaluating these and further results will provide valuable information about the modern drug experience.**

I. Introduction

Twitter has been shown to provide a means of sharing information on a variety of health-related conditions [22], [20], [18]. A number of studies have mined Twitter about issues as diverse as detecting flu epidemics [5], [8], [1], classifying and seeking advice from dental pain messages [11], [3], screening for depression and other mental health problems [9], [7], [14], [19], and tracking suicide risk factors [12], [17], [2].

Recently, work has focused on the misuse and abuse of both prescription and illicit drugs [10], [4], [13], [21]. Prescription drug abuse, in particular, has become a significant public health issue. The number of prescription drug overdose is now surpassing the combined number of people who overdosed during the crack cocaine epidemic of the 1980s and the black tar heroin epidemic of the 1970s, and is becoming the fastest-growing drug problem in the US [6]. It has been estimated that 48 million of Americans (approximately 20% of the population) age 12 and older have used prescription drugs for non-medical reasons at some point in their lifetime [15]. Even though death only occurs in the most severe cases of abuse, the negative health consequences of prescription substance abuse are many, ranging from simple drowsiness and nausea to lack of coordination, disorientation, paranoia and seizures. Furthermore, results from the National Survey on Drug Use and Health (NSDUH) indicate that almost one-third of individuals over the age of 12 who were first-time drug users in 2009 started with abusing a non-medical prescription drug [16]. Hence, prescription drugs, such as opioids, may serve as a gateway to harder, more dangerous drugs.

In this short study, we provide preliminary results about the prevalence and attitudes about illicit and prescription drugs on Twitter, demonstrating again the potential of social media in providing valuable information about important health trends and norms.

II. Methods

We selected the following set of 73 drug names, in alphabetical order: a-minus, adderall, ambien, anabolic steroids, ativan, bennies, black beauties, cannabis, cocaine, codeine, concerta, darvocet, darvon, demerol, dexedrine, dilaudid, downers, duragesic, ecstasy, fentanyl, halcion, happy pills, heroin, hillbilly heroin, hydromorphone, kadian, ketamine, klonopin, librium, lomotil, lorcet, lortab, LSD, lyrica, lysergic acid diethylamide, marijuana, mebaral, meperidine, methadone, methamphetamine, methaqualone, methylenedioxymethamphetamine, motofen, nembutal, oxycodone, oxycontin, oxycotton, parepectolin, percocet, percodan, percs, peyote, phennies, prosam, red birds, ritalin, robitussin ac, sleeping pills, sodium pentobarbital, soma, talwin, testosterone, the smart drug, tooies, tranks, uppers, valium, vicodin, vitamin R, xanax, yellow jackets, yellows, and zombie pills. These are relatively well-known drugs, both prescribed and illicit, across all schedules of the US Controlled Substance Act. Note that the list includes both official names and common/street names for a number of drugs (e.g., LSD and lysergic acid diethylamide, ecstasy and methylenedioxymethamphetamine). In the results, we aggregate counts and list them under the drug's most common name.

Using our selected drug names as keywords, and restricting to English, we used the Twitter Streaming API to filter the Twitter stream (1% publicly available) on two different occasions, from August 15th to September 23rd, 2013, and from January 28th to February 24th, 2014, giving rise to 44,233 tweets in the first period and 54,458 in the second period, for a total of 98,691 tweets. All of the tweets were entered into a MySQL database, organized around tweet information (time of creation, text, user ID, number of retweets, etc.), user information (screen name, time of account creation, description, number of followers, etc.), and geolocation data (GPS coordinates).

In order to analyze certain attitudes with respect to drugs, in particular, attempts at selling or buying drug, and explicit expressions of need for a drug, we conducted a small manual analysis on tweets with GPS coordinates for New York. Based on an examination of a little over 500 tweets, we found that "sell/selling", "buy/buying", and "need some" were the most accurate terms for capturing our target attitudes. Given Twitter's stringent 140-character limit, this is consistent with the intuition that users would likely rely on content-rich, focused words to express such attitudes. To avoid dual or mixed attitudes, the queries were designed so as to include one of the terms while excluding the other two.

As it turned out, US actor Philip Seymour Hoffman died on February 2nd, 2014, of what was immediately suspected to be, and was also publicized as, a drug overdose. It was later confirmed by the medical examiner that the actor had indeed "died of acute mixed drug intoxication, including heroin, cocaine, benzodiazepines and amphetamine." While the event is most unfortunate, it allows us to observe the impact it may have on Twitter drug conversations, especially with respect to heroin, since 70 bags of heroin were found in the actor's apartment on the day of his death.

We use simple statistics and visualization in an attempt to provide additional information about illicit and prescription drugs, their schedule, potential seasonal effect and impact of high-visibility drug-related events, and attitudes.

III. Results

The top 10 drugs mentioned in our sample are shown in Table I. The number of mentions may exceed the number of tweets as in many cases a tweet contains references to more than one drug. It is interesting to note that the top 3, with a significant margin, are illegal drugs. There are, however, 5 prescription drugs, including 2 opioids, in this top-10 group.

TABLE I
Top-10 Drug Mentions

Name	Count
Cocaine	24,820
Marijuana	23,728
Heroin	9,138
Adderall	7,771
Xanax	5,324
Codeine	4,964
Sleeping Pills	4,423
Ecstasy	3,302
LSD	3,236
Vicodin	2,138

Overall, about 65% of the drug mentions reference illegal drugs, 13% reference depressants, and a little over 9% each reference opioids and stimulants. To help assess the risk of harm and/or abuse of each drug, the Food and Drug Administration, under the Controlled Substance Act, created a schedule that assigns each drug to 1 of 5 groups based on the level of associated risk. The lower the number, the higher the risk. For example, Schedule I contains most illegal, hard drugs, such as heroin, LSD, and peyote, while Schedule V contains with very low risk of abuse, such as cough medication (e.g., Robitussin AC). Table II shows the distribution of the drug mentions in our sample according to schedule, where the schedule is known (2,627 mentions were not assigned to a schedule).

TABLE II
Drug Mentions by Schedule

Schedule	Count
I	39,659
II	35,038
IV	14,533
III	8,686
V	120

Again, the drugs associated with highest risk of harm and/or abuse seem to dominate the conversation, with 74% of drug mentions coming from Schedules I and II.

One interesting aspect of online conversations about drugs is user intention or attitude. Here, we focus our attention on 3 specific stances, i.e., whether the user seems to be trying to sell a drug, to buy a drug, or simply to express their need for a drug. The top 10 drugs mentioned with respect to a specific user's attitude are shown in Table III. Figure 1 complements Table III by showing the difference in attitude by drug.

TABLE III
Top-10 Drug Mentions with Attitude

Sell (N=1,591)	Buy (N=618)	Need Some (N=594)
Heroin (582)	Cocaine (160)	Sleeping Pills (165)
Marijuana (369)	Marijuana (139)	Adderall (80)
Cocaine (357)	Sleeping Pills (63)	Xanax (58)
Adderall (72)	Heroin (50)	Codeine (56)
LSD (69)	Adderall (42)	Marijuana (55)
Codeine (24)	Xanax (27)	Cocaine (44)
Xanax (23)	LSD (10)	Vicodin (19)
Ecstasy (23)	Vicodin (9)	Testosterone (16)
Percocet (13)	Testosterone (7)	Happy Pills (15)
Vicodin (12)	Ecstasy (5)	Heroin (12)

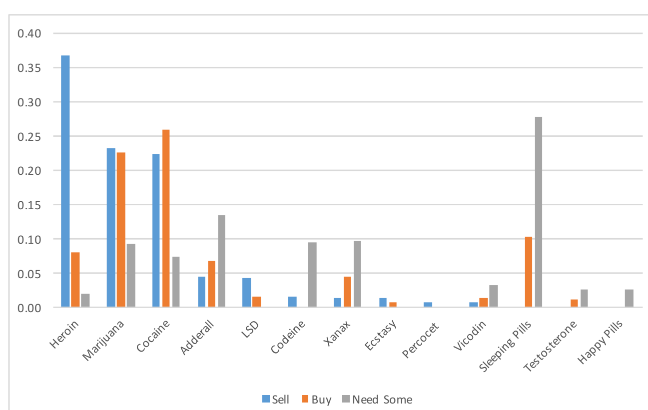

Fig. 1. Difference in Attitude by Drug

Overall, there are more mentions of selling than buying and/or needing drugs. Heroin and cocaine, which are well-known illegal (and rather hard, as well as expensive) drugs are mentioned much more often in connection with buying and selling than with needing some. Sleeping pills are the most needed drug in our sample. We also see that the most needed drugs are prescription drugs (if we include sleeping pills). Interestingly, these drugs appear lower, and in rather small proportions, in terms of selling and/or buying, probably owing to the fact that it is generally easier and less risky to obtain prescription drugs than illegal ones. In addition to doctor shopping, many individuals obtain prescription drugs from family members and friends. Marijuana, which has now been legalized in a number of states is showing little variation in terms of selling vs. buying, and appears rather high in both lists.

Finally, we were interested in looking for either seasonal or event-driven variations in drug mentions. Figure 2 shows the average number of drug mentions per day as a function of the day of the week for Summer 2013 and Winter 2014, respectively. We truncated the first and last day as we only had partial information for these days.

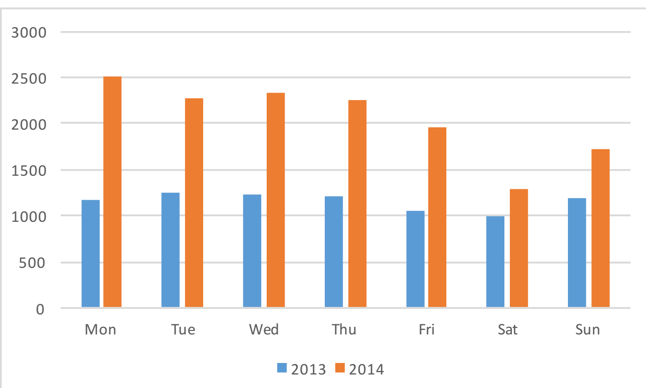

Fig. 2. Drug Mentions by Day of Week

The basic trends for both periods are consistent with prior observations, where numbers tend to dip around week-ends. Interestingly, there are generally more tweets in Winter 2014 than in Summer 2013. Almost all days in Winter 2014 have in excess of 2,000 drug mentions whereas none of the days in Summer 2013 approach that number. It is possible, as has been seen with increased prevalence of depression, that people are more likely to turn to drugs in the winter time than they are in the summer time. This needs further analysis.

As prevalence seems to vary, we also looked at whether attitudes vary with the season. We looked again at the top 10 drugs mentioned with respect to a specific user's attitude. We found no significant differences for buying and needing some. The results for selling are shown in Table IV.

While the set of mentioned drugs are identical, there is a significant change in proportions for Heroin, going from 10.5% in Summer 2013 to 45.9%, essentially dominating the conversation, in Winter 2014. As we looked closer at

TABLE IV
TOP-10 DRUG MENTIONS WITH SELL BY SEASON

Summer 2013 (N=418)		Winter 2014 (N=1,173)	
Drug	Proportion	Drug	Proportion
Cocaine	38.8%	Heroin	45.9%
Marijuana	14.4%	Marijuana	26.3%
LSD	12.2%	Cocaine	16.6%
Heroin	10.5%	Adderall	3.7%
Adderall	6.9%	LSD	1.5%
Codeine	3.6%	Xanax	1.0%
Xanax	2.6%	Ecstasy	1.0%
Ecstasy	2.6%	Codeine	0.8%
Oxycotin	2.4%	Vicodin	0.5%
Vicodin	1.4%	Oxycontin	0.5%

the data, we realized that on February 2nd, 2014, renowned US actor Philip Seymour had taken his life by what was quickly publicized as a heroin overdose. Hence, we looked at the distribution of tweets mentioning heroin and/or Philip Seymour during for the Winter 2014 data. Figure 3 shows the result. Again, we truncated the first and last day due to partial information for these days.

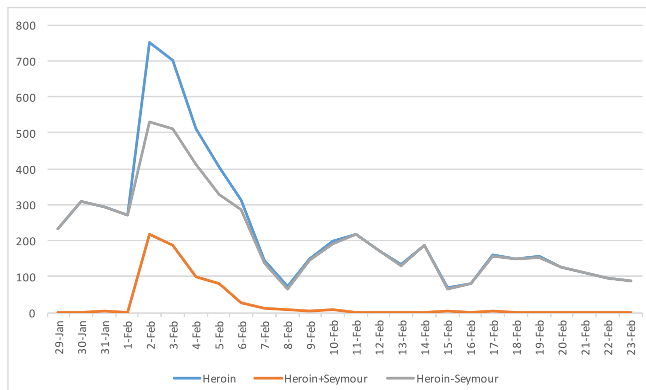

Fig. 3. Heroin Tweets With and Without Mentions of Philip Seymour - Winter 2014

Figure 3 clearly shows that the increase in number of heroin mentions in Winter 2014 is associated with Philip Seymour's suicide. The numbers spike dramatically around February 2nd and 3rd, and return to "normal" levels within the week following the suicide. This graph confirms that reactions to significant events are often reflected in social media. Note that here, most of the additional mentions of heroin were in conjunction with the word "sell." A qualitative analysis of the tweets may allow us to determine whether these were from individuals arguing against the sale of heroin (given its obvious poor consequences as shown by Seymour's death) or from individuals trying to leverage the publicity on heroin to sell more of the drug, possibly impacting normative behavior.

IV. LIMITATIONS

Only two relatively short snapshots of data were used for our analysis over time. Findings would be strengthened with data collected over a longer period of time. We performed one such analysis with the specific drug Adderall over a 6-month period [10]. In this preliminary analysis, we did not distinguish between the use of Twitter by private individuals from its use by news outlets and other official sources. Such a division with a focus on private individuals would improve the value of our results. We must be careful not to overstate the implied result that users are openly advertising the buying and selling of Schedule I drugs on Twitter. While this is likely the case, a further analysis of tweets with mentions of "sell" and "buy" is required to filter out those who may also contain irony or sarcasm, and thus not reflect actual attitude/behavior with respect to these drugs.

V. Conclusion

In this short paper, we have analyzed drug-mentioning tweets in an attempt to further inform our understanding of social media as a means to monitor conversation, and possibly attitude and behavior, around critical health issues. We have shown that, as might be expected, most of the drug mentions on Twitter relate to illegal drugs, and that these also occur in significantly higher proportions when combined with attitudes around selling and buying such substances. Interestingly, prescription drugs, including opioids, are highly represented when combined with the need to obtain such substances. Finally, we have shown that drug-related events of high visibility, such as overdoses of celebrities, are reflected in the chatter on Twitter.

It is clear that much more can be done with our data. For example, a short manual analysis of specific keywords revealed that when tweets mentioned prescription drugs, they were often comparing them to the effects of marijuana and cocaine, and many even claimed that doing regular drugs was not as bad as abusing prescription drugs. Conversely, a number of tweets were asking for advice on how to approach a doctor when trying to get a particular drug. Users mentioned they were thinking on asking a doctor for a particular drug, or tweeted about a particular drug that a doctor prescribed them. Indications of such behaviors and attitudes may inform intervention.

Other useful information may be available from links. A number of the tweets in our sample were picked up because they contained a link that a drug mentioned within the link, even though the text of the tweet had no explicit drug mentions. Links may indicate that a user may be tweeting about an event referring to a picture or a news article. Most of these links are either to photos on Instagram or to expired news articles that explained an event dealing with particular drugs. A look at a sample of these links suggested that anything white was described as cocaine (particularly shoes), appetizing goods were described as ecstasy, and articles on marijuana were usually about medical uses and legalization. Again, each of these findings warrants further investigation.

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