ANALYSIS OF DEVIANT OPIOID ADDICTION TREATMENT COMMUNITIES ON REDDIT

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ANALYSIS OF DEVIANT OPIOID ADDICTION TREATMENT COMMUNITIES ON REDDIT

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SUMMARY

As the opioid epidemic in the US continues, many addicts turn to clinically unverified, non-mainstream, deviant recovery methods to ameliorate the symptoms of withdrawal. In this study, we analyze discussion on the social media site Reddit surrounding these treatments. We apply transfer learning methods to train a classifier highly sensitive to recovery-related posts. Based on network analysis of Reddit communities (known as "subreddits"), we generate a list of subreddits where discussion of deviant addiction treatment methods is taking place. Using word embeddings and the testimony of a practicing opioid addiction clinician, we identify potential alternative opioid addiction treatment methods. Applying the classifier to subreddit post data, we generate a dataset consisting of recovery-related discourse. When applied to these posts, topic modeling methods, such as Latent Dirichlet Allocation (LDA), reveal topics discussed within the context of recovery, such as the lifestyle changes associated with kratom use.

CHAPTER 1

INTRODUCTION

Opioid addiction is a serious public health issue in the United States, with nearly 80 people dying every day from an opioid-related overdose (Centers for Disease Control and Prevention, 2012). Also known as painkillers, narcotics, or opiates, opioids are a class of drug that help relieve pain, but also have high potential for abuse and addiction. The number of deaths from opioids has quadrupled since 1999, outpacing deaths from car accidents in the US (National Safety Counsel, 2017; Seth P, 2016). Addiction to opioids, whether they be illegal street drugs like heroin or prescription painkillers like methadone or Percocet, is an unprecedented and growing public health concern that has come to be known as an epidemic.

Addiction is a multidimensional problem, making its treatment extremely difficult. Before recent changes to prescribing practices, it was more common for people suffering from addiction to compulsively seek opioid prescriptions from clinicians who are unable to stop giving them, entangling them both in a vicious cycle (Lembke 2012). Treating opioid addiction typically consists of detoxification and medically managed withdrawal followed by a formal assessment and referral to drug addiction treatment (National Institute on Drug Abuse, 2012). The cost of 60 to 90-day in-patient rehabilitation programs averages between $12,000 and $60,000 (AddictionCenter, 2017), making its cost prohibitive for many Americans without health insurance to cover it. To worsen matters, opioid addiction is highly stigmatized and addicts are frequently ostracized, making embracing and managing recovery even more difficult.

Some suffering from opioid addiction turn to alternative treatment methods and therapies as a means of recovery. Some examples of these treatments include the use of non-prescription buprenorphine and the psychoactive plants iboga and kratom. While the pharmacological properties of these substances do indicate some potential for use in ameliorating opioid withdrawal symptoms, the dangers of kratom and iboga are not well understood while buprenorphine is known to have high potential for abuse (Department of Justice, 2017), making the use of these substances outside of a clinical setting particularly risky. In other words, people are engaging in "deviant," clinically unverified methods to facilitate their goals of opioid addiction recovery.

On the social networking site Reddit, there exist subreddits promoting non-mainstream therapies for opioid addiction. Some subreddits, like r/OpiatesRecovery, are supportive of recovery through both mainstream and deviant methods. Others, like r/kratom, focus specifically on the substance in question and provide materials like dosage guides, where and how to source the substance of choice, success stories, etc. As individuals participate in these communities to learn about and discuss these alternative therapies, we can explore both their motivations for skirting traditional treatment methods as well as better understand the medical use of these under-evaluated drugs. This study identifies and analyzes the discussion of alternative opioid addiction treatments on Reddit. To do this, we propose the following two research questions:

RQ1: What alternative therapies used to try to recover from opioid addiction outside clinical supervision are being discussed?

RQ2: What topics do people discuss when engaging in opioid addiction recovery?

This study addresses the dearth of knowledge concerning how people initiate, learn about, and discuss alternative treatments for opioid addiction. Aside from poison control center data and case studies, social media platforms constitute one of the few sources of data concerning the use of these therapies. It is important to note that personal experimentation with novel substances, successful or otherwise, does not constitute rigorous scientific evidence demonstrating their harm or efficacy. However, we hope to collate personal anecdotes and experiences to generate typical narratives of encounters with these substances. These data will be gathered from Reddit communities dedicated to discussion of the use of these substances and discussion of opioid addiction recovery. We hope our work informs social networks on how communities encourage or promote these deviant drug use behaviors and medical research in understanding unorthodox ways individuals try to recover from opioid addiction.

CHAPTER 2

LITERATURE REVIEW

Opioid Addiction and Recovery

Opioid addiction is a serious public health issue in the United States, with nearly 80 people dying every day from an opioid-related overdose (Centers for Disease Control and Prevention, 2012). Also known as painkillers, narcotics, or opiates, opioids are a class of drug that help relieve pain, but also have high potential for abuse and addiction. The number of deaths from opioids has quadrupled since 1999, outpacing deaths from car accidents in the US (National Safety Counsel, 2017; Seth P, 2016). Addiction to opioids, whether they be illegal street drugs like heroin or prescription painkillers like methadone or Percocet, is an unprecedented and growing public health concern that has come to be known as an epidemic.

The opioid epidemic currently affecting the United States has its roots in the 1980s, when opioids began to be prescribed more broadly to treat chronic non-cancer pain (Nelson & Perrone, 2012). As a result, both the sale of opioid analgesics and, subsequently, the rate of overdose deaths involving opioids have quadrupled since 1999 (Department of Health and Human Services, 2016), yet there has not been an overall change in the amount of pain Americans report (Daubresse et al., 2013). Many Americans become addicted to opioids after being prescribed narcotics to treat chronic pain. Treating opioid addiction typically consists of detoxification and medically managed withdrawal followed by a formal assessment and referral to drug addiction treatment (National Institute on Drug Abuse, 2012).

While in-patient programs are quite successful at promoting abstinence among addicts (Gossop, Johns, & Green, 1986),the prohibitive financial costs and time commitment required make it an infeasible option for many, particularly among those "high-functioning" addicts trying to maintain domestic and work-related duties. Taken with evidence that alternative therapies are increasing in popularity (Ernst, 2000), these findings suggest that a historical stage has been set for the popularization of non-mainstream methods in treating opioid withdrawal symptoms.

In recent years, some people suffering from opioid addiction have reported successful amelioration of withdrawal symptoms using the poorly understood plants kratom and iboga. The leaves of the kratom plant, a tree native to Southeast Asia, have been traditionally used by manual laborers to enhance productivity and by drug users to curb the effects of withdrawal (Vicknasingam, Narayanan, Beng, & Mansor, 2010). The most prevalent alkaloids in kratom (mitragynine and 7-hydroxymitragynine) display activity on certain opioid receptors that may explain kratom's ability to ease opioid withdrawal symptoms (Babu, McCurdy, & Boyer, 2008). Iboga, a shrub native to western Central Africa, has a somewhat better understood pharmacological profile. One of its constituent alkaloids, coronaridine, has been shown to persistently reduce the self-administration of cocaine and morphine in rats (Glick et al., 1994). Some avant-garde medical practitioners have opened iboga-centered addiction treatment clinics abroad in order to expedite and motivate research on the plant (Vastag, 2002). While the baseline pharmacological properties of these plants' psychoactive components have been studied, no clinical trials have been conducted to determine their therapeutic potential in humans.

Further, creative use of drugs outside these three (kratom, iboga, buprenorphine) to cope with opioid addiction recovery is not explored in pharmacological literature.

Social Media and Understanding Health States

Across many health conditions, social media provides a community for people to get support for their health challenges. Research has also shown how social media data can be mined and analyzed to understand these factors of support.

Several factors contribute to the ability of online health support communities to successfully aid in recovering from an illness. For breast cancer support, researchers have explored how emotional and informational support affect commitment to the community (Yi-Chia Wang, 2012), and how the effect of receiving such support varies based on tenure within the community (Yang, Kraut, & Levine, 2017). Similar research has explored how congruence between what kind of support a user receives and what kind of support they desire affects membership commitment (Vlahovic, Wang, Kraut, & Levine, 2014). Support does not always promote good health behaviors, as research has shown that individuals use social media sites to support their disordered eating behaviors (Chancellor, Pater, Clear, Gilbert, & Choudhury, 2016) or their propensity for severe mental illness (Chancellor, Lin, Goodman, Zerwas, & Choudhury, 2016).

Researchers have combined the capacity to infer health states based on discourse with an understanding of online health support group dynamics to produce work tracking the stages of recovery – investigating a therapy, engaging in the therapy, relapse, recovery – as someone combats an illness. Notably, research has demonstrated the effectiveness of online forums as aids to recovery from addiction, with involvement in such communities being positively correlated with a user recovering (MacLean, Gupta, Lembke, Manning, & Heer, 2015). Other research has demonstrated that the quality of discourse affected recovery outcomes among people suffering from anorexia, with a focus on *health* being associated with recovery, and a focus on *body* being associated with the opposite (Chancellor, Mitra, & De Choudhury, 2016).

For drug addiction and abuse research on social media, other researchers have developed methods for detecting verbiage indicating drug abuse as well as various forms of mental illness. One method described was able to detect with high recall and precision instances of discussion on Twitter concerning abuse of the drug oxycodone (Sarker et al., 2016), while another found that users posting on online health support groups for opioid addiction frequently described enough symptoms to meet criteria for opioid use disorder (D'Agostino et al., 2017). Closest to our own is Park and Conway's work, which does a rudimentary analysis of opium-related discussion across all of Reddit (Park & Conway, 2017).

What distinguishes previous work from these studies is twofold. First, no work has explored alternative therapy use on social media. We do not understand why people explore these highly experimental therapies (as opposed to mainstream methods) in the first place. Second, the effectiveness of clinically unverified therapies for opioid addiction recovery has, by definition, not been established. While prior work has established the ability of online discourse to promote recovery, the community surrounding alternative therapies may have a more nuanced perspective on what constitutes recovery. For instance, someone previously addicted to painkillers may consider themselves to be in recovery after weaning off those narcotics using kratom, but from a strictly clinical perspective, her use of kratom would constitute yet another unhealthy drug dependence.

CHAPTER 3

DATA AND TERMS

Our data will come from Reddit, a popular online social media site. There, users can form communities called subreddits to discuss any topic of their choosing. Subreddits host discussion in the forms of posts on which users may comment. We gather all post data from every relevant subreddit from 2005 (Reddit's founding year) to December 31, 2017. We exclude comment data as it is unworkably noisy, while post data is generally richer and more highly contextualized. We will describe the methods of cataloguing relevant subreddits and curating this data in the Methods section to follow.

We start our analysis by focusing on r/OpiatesRecovery, one of the largest subreddits dedicated to promoting opioid recovery in all forms. r/OpiatesRecovery describes itself as, **"**…a group of people dedicated to helping each other kick the habit…We support all methods of recovery" ("r/OpiatesRecovery," 2018). Founded on April 7, 2013, the subreddit has over 16,207 posts as of the end of 2017 and 12,365 subscribers at the time of writing. Posts and comments on r/OpiatesRecovery are unique in that they may be considered ground truth of "recovery" behaviors, due to the subreddit's focus on promoting recovery in all forms. The subreddits r/methadone and r/suboxone, dedicated to discussion of their titular medicines used to treat addiction to opioids, are also suitable for this purpose. Data from these subreddits will be referred to as the **recovery dataset** and will be used to train our classifier to learn to identify opioid addiction recovery posts.

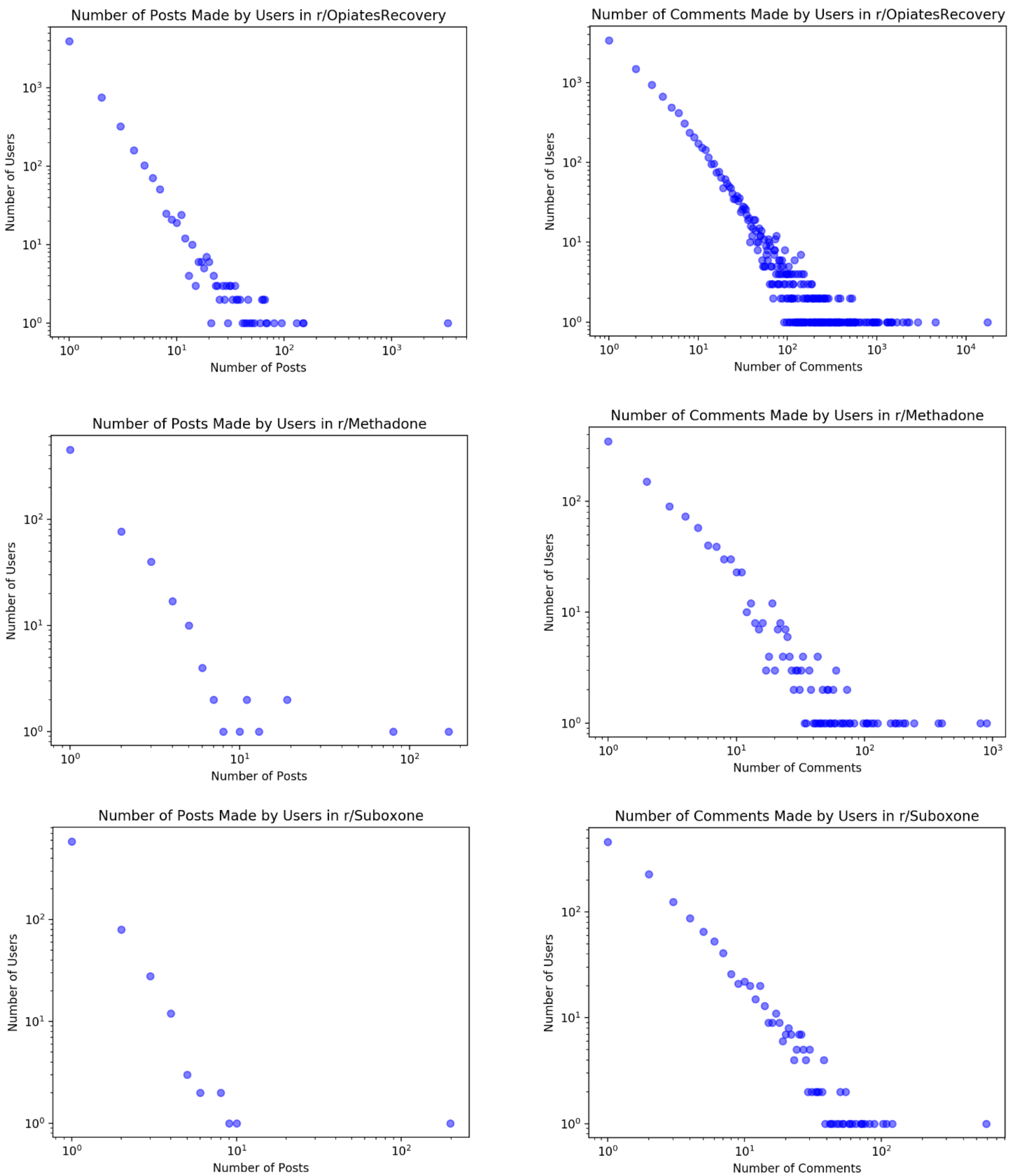

Figure 1. ***Logarithmically scaled graphs visualizing the volume of post and comment data in r/OpiatesRecovery, r/Methadone, and r/Suboxone.***

In addition to discussion in the recovery dataset, there may be recovery-related posts across various unrelated subreddits. These subreddits may be related to other drugs or substances, self-help or self-improvement, and so on. We will call data from these subreddits the **drug dataset** (Tables 2 and 3). A detailed description of how this dataset was generated can be found in the "Methods" section under "*Identifying Subreddits of Interest*." Applying a classifier sensitive to recovery-related discourse to label posts in this dataset will yield the **final dataset**.

Finally, we need to establish our **control dataset** to show the classifier what posts not related to drug-recovery resemble (Table 1). This will consist of a group of randomly sampled posts from the most popular subreddits, known as default subreddits, taken from (Saha & De Choudhury, 2017), as well as posts from selected subreddits dedicated to recreational drug use. The default subreddits provide examples of general conversation across a variety of topics. We deliberately include three drug-related subreddits in this list to make the classifier sensitive enough to distinguish between recreational and recovery-related drug use. After training our classifier using default Reddit posts as negative data and applying it to real data, we found it was not precise enough to distinguish medicinal from recreational drug use. Therefore, we opted to supplement the list of control subreddits with r/Drugs, r/Psychonaut, and r/trees, due to the volume of posts available as well as the recreational drug use-related discussion they host. The control dataset is artificially balanced to consist of 50% posts from default subreddits and 50% posts from the recreational-drug-use subreddits.

CHAPTER 4

METHODS

To determine what alternative recovery methods people are using, we must first identify drug-related subreddits from the drug dataset to analyze and identify posts within that dataset that discuss opioid addiction recovery.

Identifying Subreddits of Interest

Subreddits frequently refer to one another in their information sidebars under a “Related Subreddits” header, providing a metric for the relatedness or similarity of communities. We conducted a breadth-first search from sidebar to sidebar starting at r/OpiatesRecovery to a depth of 2 on November 8, 2017. A depth of 1 provides the subreddits suggested by r/OpiatesRecovery (also known as children), while a depth of 2 provides the subreddits suggested by the subreddits identified in a depth of 1 (or grandchildren of r/OpiatesRecovery). A depth of 3 or more provides similar information but results in an incomprehensible web of nodes and edges due to the exponential increase in nodes and edges. Therefore we restrict our breadth-first search analysis to a depth of 2.

This procedure yielded a graph which, after removing the r/OpiatesRecovery node, leaves four connected components consisting of:

1. Self-improvement, fitness, and cannabis subreddits (Table 2)
2. Illicit (non-cannabis-specific) drug use subreddits (Table 3)
3. r/suboxone, and
4. r/methadone.

Some subreddits in this graph bore no relevance to addiction recovery. To address this, we pare down this list of subreddits by applying a rating task with criteria:

1. The subreddit must pertain, based on content referred to in its sidebar, to any psychoactive drugs or substances catalogued by Erowid[1], or
2. The subreddit must pertain to recovery from drug addiction.

To refine the accuracy of our list of drug-related subreddits, three raters determined whether they believed each subreddit from the sidebar crawl pertained to the given criteria and found they agreed on the drug-relevancy of almost all subreddits – there were only three disagreements in total. Disagreements were resolved through further discussion. This yielded a list of 81 subreddits. A clinician with expertise in addiction management contributed 3 more alternative treatment methods we had not yet seen, of which 2 had corresponding subreddits to which we had access. The final list of 83 subreddits, whose post data comprises the drug dataset, is shown in **Error! Reference source not found.**

RQ1: Identifying Alternative Therapy Drug Names Using Word Embeddings

To identify potential alternative drug therapies, we took the following approach. First, working in conjunction with our opioid addiction expert, we made a list of known alternative drug therapies for opioid addiction recovery. This list included yohimbe, iboga, kratom, pregabalin, gabapentin, phenibut, agmatine, modafinil, and several benzodiazepines. Using the gensim natural language processing library, we generate a

[1] https://www.erowid.org/

word embedding using the continuous bag of words training algorithm on all data in the drug dataset. For each drug in the list, we query the word embedding for the 20 most similar words to the drug by cosine similarity. The result (20 similar words per drug) was provided to the expert, who labeled the drugs according to their pharmacological effects and possible use in opioid addiction recovery.

RQ2: Finding Recovery Posts Using Transfer Learning

Once we have identified subreddits where recovery-related discourse is taking place, transfer learning methods let us identify discussion data as related to recovery, as well as compensate for the relatively low amount of data available in the recovery dataset – r/OpiatesRecovery had 16,207 posts, r/Methadone had 1,225 posts, and r/Suboxone had 1,139 posts. Analyzing posts in the recovery dataset moves us towards answering our research questions, but 18,571 posts contributed to this community over its lifetime is an insufficient amount. Posts across disparate subreddits may contain a mix of non-recovery- and recovery-related discussion. Rather than manually review and label thousands of posts and comments, we apply our classifier, sensitive to recovery-related discussion, to computationally label data for us. We train the classifier on posts from the recovery dataset and the control dataset.

The features we provided to the classifier consisted of word count, parts of speech tagging, and the top 1,000 term frequency-inverse document frequency (TF-IDF) features across the control and recovery datasets. First, we generated lists of words from the recovery and control corpora by lowercasing the text, removing English stop words from a list provided by scikit-learn (a machine learning and data analysis library), and removing punctuation to clean the data. This preprocessing removes common words such as “the” and “is,” as they convey little meaning and slow down processing time. We then determined the TF-IDF scores of words in each corpus to generate two lists containing the words most specific to each corpus. The value for each TF-IDF feature was the number of occurrences of that word in the post title or text, normalized by the number of words in the title and text combined for that post. The top 1000 unique TF-IDF terms across both corpora are used as the classifier’s features. We also filtered words of length 2 or less because these were fragments of conjunctions such as ‘nt’ and ‘ll’ which by themselves do not convey meaning. To make sure the classifier didn’t overfit on the word “recover” specifically, we filtered any terms that started with the word “recover” (i.e. “recovery”, “recovered”, “recoverer”, etc.). The part of speech features represented every part of speech tag represented in NLTK’s UPenn Tagset, resulting in 45 features. The part-of-speech feature values were calculated by counting the number of occurrences of each part of speech tag in the post or comment, normalized by the number of words in that comment or post. In total, we generated 1,045 features to train on.

RQ2: Topic Modeling with LDA and Analysis

We ran the classifier on the drug dataset to identify posts discussing drug recovery in those subreddits, generating the final dataset. To discover topics discussed in the context of recovery and answer RQ2, we apply topic modeling methods. Topic modeling is an unsupervised approach to computationally discovering related clusters of words, or topics, in text documents. We use Latent Dirichlet Allocation (LDA) as it allows for words to be mapped to several topics without being mutually excluded. For example, the word “deal” could refer to the sale of illicit substances, e.g. “deal drugs,” or to struggling with opioid addiction, e.g. “deal with withdrawal,” and thus appear in two different topics. Before passing posts in the final dataset to LDA, we remove English stop words found in the Natural Language ToolKit's (NLTK) list of stop words supplemented by a list of spurious words (don't, should, etc.), treating each post as a bag of words to be passed to the model. LDA does not provide names or labels to the categories it discovers. To identify the topics discovered by LDA, three raters work to inductively name each topic by qualitatively interpreting the terms present in each topic.

CHAPTER 5

RESULTS

RQ1: Potential Alternative Therapy Drugs

Table 1. ***Drugs uncovered through the use of expert testimony, word embeddings, and expert labeling.***

Drugs, Plants, and Vitamins Potentially Used in Alternative Treatment Methods			
neurontin	iboga	magnesium	ibogaine
ergot	librium	adderall	bacopa
tramadol	zopiclone	pyrazolam	L-tyrosine
vistaril	mucuna	mirtazapine	memantine
lyrica	valium	kpin	L-arginine
modafinil	kanna	ergotamine	DXM
loperamide	dilaudid	4FMPH	cordyceps
vinpocetine	piracetam	klonipin	turmeric
vyvanse	belladonna	phenobarbital	lorazepam
yohimbine	temazepam	ultram	aniracetam
taurine	scopolamine	curcumin	ginkgo
DLPA	noopept	syrian	EGCG
amitriptyline	harmalas	DPH	clonazolam
phenylpiracetam	peyote	diazepam	ephedrine
corydalis	cyclobenzaprine	diclazepam	psilocybin
ambien	agmatine	datura	5HTP
adrafinil	phenibuttianeptine	vicodin	ashwagandha
buspirone	passionflower	piperine	gabapentin
ayahuasca	trazodone	citrulline	semax
fioricet	selegiline	baclofen	etizolam
mulungu	aya	N-acetylcysteine	kratom
kava	pruriens	xanax	LSA
yohimbe	BSO	clonazepam	theracurmin
propanolol	zolpidem	methylphenidate	alprazolam
larginine	pregabalin	hydroxyzine	L-theonine
seroquel	khat	ativan	rhodiola

Many of the substances observed are either plants or plant-based substances that provide L-DOPA to the body or whose mechanism of action increases the bioavailability of L-DOPA, where L-DOPA is the metabolic precursor to dopamine. Gabapentin and pregabalin are anticonvulsant drugs used as substitutes for opioid painkillers that are possibly being diverted for illicit use in alternative therapies. Benzodiazepines (alprazolam, clonazepam, lorazepam, etc.), a class of sedative drugs, may be being used similarly. Cannabis and the psychedelic drugs (LSD, ibogaine, psilocybin, etc.), have been observed to be used for treating opioid addiction, perhaps due to their ability to elicit transformative “trip” experiences.

RQ2: Recovery Classifier Performance

We train a random forest (RF) classifier with 10 estimators using the gini splitting criterion. This produced an accuracy of 0.961, precision of 0.907, recall of 0.677, and F1 score of approximately 0.775 when trained on 119,149 instances and tested on 51,060 instances. The training and testing datasets consisted of 10% recovery posts and 90% control posts. Currently, the classifier overenthusiastically labels posts as relating to recovery from opioid addiction. Feature correlations determined by the classifier give us an idea of what it is learning and why it may be underperforming. In many cases, semantically ambiguous words are determined to be highly correlated to recovery signals, leading to a high false positive rate. For instance, the words “sub” and “subs” have high feature correlations, but could refer to “suboxone,” “subreddit,” or “subscriber.” One of the most highly correlated terms, “day,” is self-evidently ambiguous. Additionally, it is likely that the classifier is identifying any signals related to drugs or distress as pertaining to recovery. A significant portion of the topics yielded by our LDA modeling of the final dataset pertained to discussion by vape hobbyists or discussion of cannabis (means of consumption, subjective effects, etc.). Nonetheless, the classifier labeled posts with sufficient sensitivity as for LDA to be able to discern relevant discourse.

RQ2: LDA Results and Qualitative Analysis

Table 2. ***Topics generated by LDA from the final dataset deemed relevant by raters to discussion of recovery.***

LDA Topic Modeling Output and Rating		
Topic number	Words relevant to topic	Rater-assigned label
10	Life, feeling, gram, grams, living, heavy, everyday, changed, healthy, lives, dreams, forever, road, ride, slowly, depressed, kratom, strange, knowing, sorry	Kratom and life experience
12	Long, clean, alcohol, pain, short, cleaning, coils, story, yall, doctor, running, term, bottles, prescribed, hospital, benzos, kill, generally, toking, watts	Getting clean
21	Family, away, movie, type, drinking, anxiety, sense, red, Sunday, issues, public, depression, having, related, games, 510, heart, based, tea, die	Mental health and alcohol
25	Days, week, weeks, finally, break, saying, half, ago, phone, fact, number, sent, cut, kit, wife, service, passed, stop, beginning, went	Stopping drug use
28	Day, suggestions, hot, daily, Friday, work, quit, wake, cold, Monday, pics, seriously, date, proud, nearly, worked, withdrawal, sleeping, heart, sorry	Quitting and withdrawal

We varied the number of topics generated over several runs of LDA on the final dataset. We qualitatively determined that LDA generates topics most coherently after requesting 50. After drawing 20 words related to each topic, three raters inductively gave a name to each topic. Several topics that emerged are particularly relevant (see **Error! Reference source not found.**). It may be inferred that a topic's presence is indicative of its prevalence within the dataset. Notably, three topics pertained to cessation of drug use, but in separate domains. Topic 12 pertained to the clinical side of ending drug use (prescriptions and hospital or doctor visits), topic 25 pertained to the temporal side of ending drug use (counting days since ending use), and topic 28 pertained to the subjective side of ending drug use (withdrawal and other negative side effects). Interestingly, the cloud of terms associated with “kratom” seem to suggest that its use, for better or worse, is associated with a dramatic change in lifestyle.

CHAPTER 6

DISCUSSION

Our work presents novel insights into the growing popularity of alternative treatment methods for opioid addiction. First, we believe clinicians will benefit from an advanced understanding of addiction treatment methods pursued outside a clinical setting. As it stands, many practicing clinicians are aware of the proliferation of deviant treatment methods currently underway, yet do not have any grounded evidence of their use by both non-patients as well as what their in-patients may have attempted in the past. Our data reveal users discussing new treatments such as kratom, iboga, kanna, and yohimbe, as well as the off-label use of modern pharmaceuticals such as loperamide and benzodiazepines. As a result, we are discovering both clinically underexplored treatments like kratom as well as unexpected uses of modern medicines. We hope this work drives future research on understanding the effectiveness and reliability of these methods. For future work, it is possible that the "crowd-sourced" knowledge accrued in these online communities may prove useful in determining dosing protocols in future clinical research with, for instance, kratom. At a minimum, our work demonstrates another means of conducting mass toxicovigilance by recruiting social media platforms as a data source.

Second, we hope to introduce some nuance into the discussion surrounding addiction as a mass public health issue. A host of factors play against addicts seeking treatment via traditional means. On top of the cost of rehabilitation programs in terms of time, money, and enduring withdrawal, an addict undergoing such treatment effectively broadcasts his or her highly stigmatized condition to the public. Such people find themselves in a double bind – do they avoid the potential embarrassment of openly seeking treatment, or do they take the plunge? To complicate things, public perception of opioids is somewhat misinformed – prescription pain killers and heroin are nearly equivalent pharmacologically, yet addiction to one elicits an entirely different social stigma than addiction to the other. That in mind, it is little wonder that many addicts turn to alternative treatment methods permitting them a degree of autonomy and privacy they would not otherwise enjoy.

The tragedy of mass-scale opioid addiction and its impacts on families and communities demands we afford addicts greater dignity, starting by clarifying the distinction between recreational and medicinal drug use. Currently, the scarcity of research on these off-the-map treatment methods makes drawing that distinction a thorny issue. We hope to shed light on the efforts of addicts earnestly trying to treat their condition. However, we must be cautious of legitimizing reckless drug use or the use of poorly understood substances, which would only blur the line between recreational and medicinal drug use even further. We believe the situation demands spreading awareness of these trends to promote public awareness and motivate future research.

APPENDIX

Table 3. ***Default subreddits containing discourse across a broad variety of topics and recreational drug use-related subreddits.***

Subreddits in the Control Dataset		
r/AskHistorians	r/funny	r/Music
r/AskReddit	r/gadgets	r/NeutralPolitics
r/askscience	r/gaming	r/news
r/aww	r/history	r/Psychonaut
r/books	r/jokes	r/technology
r/Drugs	r/Jokes2	r/trees
r/food	r/movies	r/UpliftingNews

Table 4. ***Self-improvement, fitness, and cannabis-related subreddits made up one connected component of a graph derived from a 2-deep breadth-first search from the "Related Subreddits" section of one subreddit to another, starting at r/OpiatesRecovery.***

Self-Improvement, Fitness, and Cannabis Subreddits				
/r/quotesporn/	/r/zenhabits/	/r/meditationpapers/	/r/life/	/r/supplements/
/r/kickassday/	/r/atheisttwelvesteppers/	/r/pornfree/	/r/firewoodvapes/	/r/nonconformists/
/r/fixmydiet/	/r/quittingkratom/	/r/keto/	/r/waxpen/	/r/truegetmotivated/
/r/dietetics/	/r/fitness/	/r/glutenfree/	/r/studies/	/r/gotmotivated/
/r/electronic_cigarette/	/r/leaves/	/r/modquittingkratom/	/r/liferpg/	/r/getdisciplined/
/r/slackerrecipes/	/r/allcapsmotivation/	/r/recipes/	/r/youcandoit/	/r/30daysit/
/r/challengeaccepted/	/r/getmotivated/	/r/getresults/	/r/vapormax/	/r/200situps/
/r/accountabuddyprogress/	/r/calmhands/	/r/motivationalpics/	/r/redditorsinrecovery/	/r/davincivaporizer/
/r/danceperformance/	/r/healthyfood/	/r/kaizenbrotherhood/	/r/boundlessvapes/	/r/lifegoals/
/r/meditation/	/r/spiritual/	/r/100pushups/	/r/herbalaire/	/r/accomplishedtoday/
/r/heartohelpus/	/r/entshop/	/r/howtonotgiveafuck/	/r/koans/	/r/advice/
/r/150dips/	/r/decidingtobebetter/	/r/groupsit/	/r/fitmeals/	/r/vegrecipes/
/r/crossfit/	/r/c25k/	/r/getmotivatedbuddies/	/r/publichealth/	/r/leangains/
/r/open_up/	/r/ufyh/	/r/stopgaming/	/r/noexcuses/	/r/7thfloor/
/r/explainlikeimscared/	/r/taoism/	/r/grasshoppervape/	/r/meditationpics/	/r/purpose/
/r/getoutofbed/	/r/athleticents/	/r/progresspics/	/r/trailmeals/	/r/healthhub/
/r/volcanovaporizer/	/r/salesmotivation/	/r/kundalini/	/r/ukentexchange/	/r/selfhelphub/
/r/buddhism/	/r/meditationpractice/	/r/integral/	/r/carpediem/	/r/yoga/
/r/cannabisextracts/	/r/keepwriting/	/r/getemployed/	/r/motivation/	/r/entexchange/
/r/alcoholism/	/r/cooking/	/r/vegetarianism/	/r/stopdrinking/	/r/dancetutorials/
/r/audiomeditation/	/r/giveme40days/	/r/nosurf/	/r/nutrition/	/r/addiction
/r/stopditching/	/r/socialskills/	/r/dynavap/	/r/butanevaporizers/	/r/sdirc/
/r/zen/	/r/cannabis/	/r/sdlocal/	/r/pescetarian/	/r/inspirationscience/
/r/ploompax/	/r/manprovement/	/r/getstudying/	/r/mflb/	/r/getoutandvape/
/r/trees/	/r/tokespot/	/r/portabledabs/	/r/selfhelp/	/r/backonyourfeet/
/r/stoicism/	/r/health/	/r/getwell/	/r/thepdchallenge/	/r/secularsobriety/
/r/motivatedmusic/	/r/abv/	/r/petioles/	/r/musicforconcentration/	/r/askdrugs/
/r/90daysgoal/	/r/alanon/	/r/loseit/	/r/paleo/	/r/dating_advice/
/r/improvementhub/	/r/projectreddit/	/r/eldertrees/	/r/nofap/	/r/mentors/
/r/200squats/	/r/sdbookclub/	/r/stonerengineering/	/r/productivity/	/r/affirmations/
/r/motivateme/	/r/minimeals/	/r/getting_over_it/	/r/lifeimprovement/	/r/trichsters/
/r/arizer/	/r/smartrecovery/	/r/stopsmoking/	/r/asmr/	/r/needacoach/
/r/declutter/	/r/confidence/	/r/pinnaclepro/	/r/selfimprovement/	/r/gainit/
/r/todayistruggled/	/r/gm/	/r/vapebonging/	/r/goboof/	/r/vaporents/
/r/simpleliving/	/r/coolcrosby/	/r/feelgood/	/r/mentat/	
/r/vegan/	/r/motivationvideos/	/r/craftymighty/	/r/straightclub/	
/r/treedibles/	/r/stopselfharm/			

Table 5. ***Illicit, non-cannabis-specific drug use subreddits made up another connected component of the graph we generated (see Table 2 caption).***

Illicit (Non-Cannabis-Specific) Drug Use				
/r/benzodiazepines/ /r/benzorecovery/ /r/drugsarebeautiful/ /r/rcsources/ /r/drugscirclejerk/ /r/stimcirclejerk/	/r/drugs/ /r/tripsit/ /r/pillhead/ /r/opiatesmemorial/ /r/drugtesthelp/	/r/glassine/ /r/opiates/ /r/darknetmarkets/ /r/reagenttesting/ /r/mdma/	/r/pharms/ /r/stims/ /r/fentanyl/ /r/carfentanil/ /r/askadoctor/	/r/drugnerds/ /r/psychonaut/ /r/tryptonaut/ /r/methodhub/ /r/researchchemicals/

Table 6. ***Remaining subreddits after rating the subreddits listed in Table 2 and adding the drug subreddits contributed by the clinician expert on opioids.***

Final Candidate Subreddits				
r/drugs r/7thfloor r/abv r/addiction r/alanon r/alcoholism r/arizer r/askdrugs r/atheisttwelvesteppers r/athleticents r/benzodiazepines r/benzorecovery r/boundlessvapes r/butanevaporizers r/cannabis r/cannabisextracts r/carfentanil	r/carfentanil r/craftymighty r/darknetmarkets r/davincivaporizer r/drugnerds r/drugsarebeautiful r/drugscirclejerk r/drugtesthelp r/dynavap r/eldertrees r/electronic_cigarette r/entexchange r/entshop r/fentanyl r/firewoodvapes r/gabapentin	r/getoutandvape r/glassine r/goboof r/grasshoppervape r/herbalaire r/leaves r/mdma r/methadone r/mflb r/modquittingkratom r/opiates r/opiatesmemorial r/petioles r/pharms r/pillhead r/pinnaclepro	r/ploompax r/pregabalin r/portabledabs r/psychonaut r/quittingkratom r/rcsources r/reagenttesting r/redditorsinrecovery r/researchchemicals r/sdbookclub r/sdirc r/sdlocal r/secularsobriety r/smartrecovery r/stimcirclejerk r/stims	r/stonerengineering r/stopdrinking r/stopsmoking r/supplements r/tokespot r/treedibles r/trees r/tripsit r/tryptonaut r/vapebonging r/vaporents r/vapormax r/volcanovaporizer r/waxpen r/suboxone r/kratom r/heroin r/quittingkratom

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