Discovering Alternative Treatments for Opioid Use Recovery Using Social Media

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ABSTRACT

Opioid use disorder (OUD) poses substantial risks to personal well-being and public health. In online communities, users support those seeking recovery, in part by promoting clinically grounded treatments. However, some communities also promote clinically unverified OUD treatments, such as unregulated and untested drugs. Little research exists on which alternative treatments people use, whether these treatments are effective for recovery, or if they cause negative side effects. We provide the first large-scale social media study of clinically unverified, alternative treatments in OUD recovery on Reddit, partnering with an addiction research scientist. We adopt transfer learning across 63 subreddits to precisely identify posts related to opioid recovery. Then, we quantitatively discover potential alternative treatments and contextualize their effectiveness. Our work benefits health research and practice by identifying undiscovered recovery strategies. We also discuss the impacts to online communities dealing with stigmatized behavior and research ethics.

CCS CONCEPTS

• **Human-centered computing → Collaborative and social computing**; **Social media**;

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KEYWORDS

opioid use disorder; recovery; Reddit; alternative treatment; addiction; online communities

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1 INTRODUCTION

Opioid use disorder (OUD)[1] is one of the most pressing public health concerns today. In the United States alone, OUD has been deemed an epidemic with substantial resources funding its treatment [25]. Over 11 million Americans misuse opioids daily; in 2017, deaths from opioid overdoses (42,000) outnumbered car accident fatalities [25].

Opioids are a class of drugs that act on the central nervous system to relieve pain [28]; this includes illicit drugs such as heroin and prescribed painkillers such as oxycodone and codeine. Although opioids have numerous pharmaceutical uses, regular use of opioids holds high risk for OUD with severe social and medical consequences and potential for lethal overdose [28, 6]. Clinical OUD recovery combines psychotherapy with prescription maintenance medication, such as methadone or suboxone [6]. Despite favorable outcomes, OUD recovery is lengthy and physically taxing [28].

Social media has emerged as places for support around recovery experiences [92, 15]. For substance abuse disorders like OUD, research shows individuals turn online to promote recovery efforts by posting to addiction recovery spaces [10, 56] – examples include Forum77 [56] and communities for twelve-step programs like Narcotics Anonymous [83, 81].

[1]We use the more clinically validated, non-stigmatizing OUD instead of "opioid addiction" to refer to this disease.

However, other online communities promote clinically unverified, alternative methods to ameliorate withdrawal symptoms, manage detoxification, and recover from OUD. This includes off-label use of prescription medication as well as substances like kratom and iboga. In this paper, we call these clinically unverified and medically unsupervised alternative treatments "ATs".[2]

The use of ATs for recovery is both controversial and poorly understood from a clinical perspective [8, 80]. Some report successful amelioration of withdrawal symptoms [9], while others report physical dependence and dangerous side effects [65, 95, 64]. While some ATs may have potential to ameliorate withdrawal symptoms, there have been no clinical trials or rigorous medical research establishing these as effective OUD recovery treatments. Further, there is no grounded list of ATs for use in studying or treating OUD.

Compounding these concerns are issues of stigma affecting disclosure of OUD and AT use. OUD and addiction are highly stigmatized; for those labeled an "addict," this stigma causes many negative outcomes, including embarrassment and unwillingness to enter treatment [53]. Especially when OUD behaviors are criminalized, sufferers may feel reticent to share with clinicians, researchers, and caregivers like family and friends [65]. This makes it difficult to gather data to understand practices around ATs from sufferers through interviews or patient disclosures.

Our Contributions. We use social media data to understand the use of ATs for OUD recovery. Behaviors such as drug use, self-reported symptoms, and dependence potential can be gathered from online communities thriving on social media that can be studied with computational techniques. Pseudonymous social media platforms also encourage disclosure of stigmatizing social experiences without worry of negative consequences of disclosure [2]. Accordingly, we use social media data on first-hand self-reports to study AT use to overcome the difficulties of soliciting information from those struggling with stigmatizing experiences such as OUD. Understanding these behaviors can ultimately provide better information on ATs, support better health research that promotes harm reduction, and improve online communities that support OUD recovery.

This paper examines Reddit to study ATs in OUD recovery. Our study considers two research questions:

RQ1: *How can we identify conversations in online communities where OUD recovery is discussed?*

RQ2: *How can we discover specific drugs used as ATs and understand their effectiveness and the risks/benefits of use?*

[2]We considered using "alternative recovery strategies" to refer to clinically unverified and medically unsupervised chemicals to aid recovery efforts. Instead, we use "alternative treatments" since "strategy" encompasses lifestyle/behavior changes, and our focus was on alternative chemical substances for recovery.

To address these research questions, we present the first large-scale social media study of ATs in OUD recovery, drawing on advances in machine learning and computational linguistics. We partner with an addiction research scientist who is also a clinical psychologist throughout the research process. First, we develop a transfer learning approach to automatically infer Reddit content related to OUD recovery with 79% accuracy on expert labeled data. This classifier successfully discovers over 93,000 posts on OUD recovery, drawn from 63 expert-curated communities of substance use. For RQ2, we combine word embedding models and manual annotation to identify specific ATs. Finally, we present a qualitative analysis contextualizing practices of AT use.

Our work provides a preliminary list of ATs and an analysis of practices of use, such as the creation of "kits" or "stacks" of drugs used in concert to combat OUD and ameliorate withdrawal symptoms. Our research demonstrates the complexities of ATs, as many carry medical risks and addiction potential. This improves our understanding of ATs for better clinical research and treatment of OUD. In addition to providing insights for health efforts, this work provides new methodologies for HCI to study traces of online behavior around stigmatizing experiences, complementing ongoing research in the field [3, 2, 81]. Finally, we discuss the challenges of designing intervention systems on social media in OUD recovery that must be tempered by concerns for stigma, and the ethics of researching OUD and stigmatizing topics on social media.

Ethics and Privacy. In many countries, non-prescribed opioid use is illegal and can cause reputation damage and criminal investigation. All data was publicly available when gathered, and the researchers had no interactions with users–therefore, our research did not qualify for ethics board review at our institutions. However, we are obligated to protect the privacy and anonymity of the users in our dataset because of these risks. We adopted several data protections, elaborated in the paper's Discussion section, drawing on prior work in HCI on sensitive populations [56, 3, 14]. Our findings *should not be* interpreted to suggest which ATs are better, more effective, or clinically valid.

2 RELATED WORK

Traditional and Alternative OUD Recovery

Opioids can be highly addictive with prolonged use, and their euphoria effects attract both recreational use as well as dependence after medical use [6]. Overdosing on opioids can cause unconsciousness, respiratory failure, and death, especially when combined with alcohol or benzodiazepines [28].

Modern OUD recovery involves opioid replacement therapy with less dangerous opioids like methadone or buprenorphine/Suboxone, combined with psychotherapy, sober living communities, and/or attendance at twelve step programs [93].

These techniques are clinically verified to facilitate sobriety and are more successful than complete abstinence [1, 37].

While inpatient programs can successfully promote sobriety [37], OUD recovery is difficult. While not necessarily lethal, withdrawal can produce severe flu-like symptoms that can last for weeks or months, and can cause significant mental distress that increases risk of dangerous symptoms like paranoia and suicidality [28]. There are also financial and social factors complicating access to and success in recovery. Coverage and cost of recovery treatments strongly depend on location, insurance status, and type of treatment [11]. Shame surrounding addiction causes many to hide their disease, and the stigma of being labeled an "addict" prevents individuals from seeking treatment [67].

Although ATs in OUD have existed for decades [80], internet access has increased awareness of these drugs and provided more convenient access [8, 45]. Kratom and iboga are the most popular and well-studied of ATs [43], with kratom's popularity dramatically increasing recently [9, 34]. Kratom is commonly adopted for alleviating opioid withdrawal symptoms or as a substitute for other substances [9, 94, 80]. In exploratory studies, kratom has been reported to produce pain-relieving and mood-stabilizing effects [80, 75]. Another popular AT is iboga/ibogaine [79], shown to reduce self-administration of cocaine and morphine in rats [35].

While baseline pharmacological properties of kratom and iboga have been explored in case studies [39], human clinical trials do not exist, and thus the safety and therapeutic effectiveness of these ATs is unknown. Notable negative side effects have been reported, including risks for dependence and addiction [95, 91], and seizures and coma from drug interactions [64]. Importantly, there is no empirically grounded resource of ATs (verified or unverified) for OUD recovery. This is detrimental to recovery, as professionals overseeing detoxification and behavioral interventions have limited insights of how ATs impacts patients and their safety.

Aside from poison control center data and case studies, social media constitutes one of few data sources for AT use. We gather data from Reddit and use computational analyses of self-reported substance use to discover these ATs.

Digital Pharmacovigilance

A growing body of research has used digital traces to understand public health concerns about physical, mental, and behavioral health [72, 24, 22]. The area of "digital pharmacovigilance" combines these digital traces and insights from social computing, digital health studies, natural language processing, and information retrieval to study self-reported use of drugs and related events [97, 85, 47]. In a pioneering work in this space, Frost et al examine how data from PatientsLikeMe can identify off-label use of certain medications [32]. Other work in digital pharmacovigilance has focused on detecting adverse drug reactions [102, 66, 85, 98], health misinformation [33], illicit online pharmacies [45], trends of non-medical prescription drug use [4, 71], identifying new drug slang [90], and anonymous social media in promoting substance use [49].

Studies of opioids have used Internet data to explore their use and abuse. In a partnership with Erowid (a major drug encyclopedia), real-time trends of searches of opioids like oxycodone were tracked [99]. Internet searches for different types of heroin have been correlated with emergency department visits for heroin overdose [103]. On Twitter, researchers have examined regional differences in opioid discussion [38] and tracking drugs by name [86]. Fan et al build a classifier on Twitter to identify those suffering from OUD [31]. Park and Conway have explored opioid mentions [70] and link-sharing behaviors [69] on Reddit. Qualitative work has also explored prescription drug abuse [89], abuse of #codeine on Instagram [19], and how one Reddit community supports clinically grounded recovery behaviors [23].

We draw on data collection techniques and methods from digital pharmacovigilance to unobtrusively study ATs in OUD recovery.

Substance Use and Recovery in HCI

In HCI, there is interest in mental and behavioral health challenges, including substance use and recovery efforts. Early work in this space focused on identifying social media displays of alcohol abuse by young adults [26, 62, 59, 96, 48], interventions for binge drinking [63, 52], and motivations for illicit substance use like cannabis [12, 60]. Relevant to our research topic, Shutler et al provided an early qualitative analysis of prescription drug abuse on Twitter [89], while Scott et al provided opportunities to reduce prescription drug abuse by leveraging social media platforms [77].

Several studies have examined technology-mediated peer support for substance use disorder recovery. Campbell and Kelly studied the use of early mobile phone support groups for those in Alcoholics Anonymous [10]. Recently, in work led by Rubya and Yarosh, they examined peer support for substance use disorder recovery meetings through video chat [83, 81], finding that video chat support groups balance needs of immediacy and convenience while also providing useful support. New work by these researchers also examines patterns of anonymity in recovery communities [82]. Finally, Schmitt and Yarosh conducted participatory design workshops to understand how to build technological interventions in substance use disorder recovery [87].

However, computational studies of substance use or recovery behaviors in HCI are limited. Research by Tamersoy et al demonstrated how linguistic cues on Reddit can indicate a user's cessation of alcohol and tobacco use, as well as their risk for relapse [92], and Kornfield et al examine language use correlating to relapse in alcohol use disorder [51, 50]. Chancellor et al demonstrate how discourse patterns can align with known measures of anorexia recovery on Tumblr [15]. Closest to our work is Maclean et al, who examine recovery trajectories from substance use disorder, demonstrating positive correlations between forum use and recovery [56].

We build on this prior work by exploring ATs, both in identifying recovery behaviors at-scale and contextualizing the use of ATs for OUD recovery.

3 DATA

We use data from Reddit, a social media and content curation site with discussion on many topics (including health, recovery, and drug use), organized into coherent communities called "subreddits." Drug behaviors about OUD recovery occur across many subreddits, not just those related to recovery. If we limited our study to only one community, we would exclude discussions of less common ATs popular in other communities. However, not all discussions across all drug subreddits relate to OUD recovery. The subreddit r/opiates, for example, discusses both opioid abuse as well as recovery journeys. To identify ATs across Reddit, we combine snowball sampling of drug-related communities for coverage and human annotations for precision. An overview of this process is in Figure 1.

Data Collection

We started at the largest OUD recovery community on Reddit, r/OpiatesRecovery, described as, "*a group of people dedicated to helping each other kick the habit*." [78] As of September 2018, this subreddit had more than 14,000 subscribers. The following is a paraphrased post on this subreddit: "*I posted a few times in the past but always relapsed shortly thereafter. For the first time in such a long time, I have managed to put together 10 days clean from [heroin]*".

We capitalize on the Reddit design affordance of a *sidebar*, a customized area with rules, links to resource pages, and importantly, links to related subreddits. We conducted a breadth-first search across sidebars for related subreddits to a depth of two in November 2017, starting at r/OpiatesRecovery. We experimented with deeper search depths, but they identified many subreddits unrelated to drug use. Then, we supplemented additional subreddits suggested by our addiction research scientist, including those about opioids (fentanyl, carfentanil, heroin), non-opioid pain relievers (pregabalin), and OUD recovery drugs (methadone, suboxone, naltrexone). After deduplication, we had 225 candidate subreddits. For this, we used Reddit's native subreddit search engine[3].

Rating Task. To filter these 225 subreddits to those related to drug use, we adopt a manual rating approach, designed with input from our addiction research scientist. To be included, the subreddit must meet one of two criteria: 1) the subreddit's topic must be about substances considered psychoactive by Erowid [29] or Psychonaut Wiki [76], excluding tobacco and alcohol; or, 2) the subreddit discussed behaviors related to Rule 1, such as recovery or sourcing/marketplaces.

Three raters explored each subreddit and decided if it met either criteria. All raters are social computing researchers. Two have extensive experience in researching social media and mental health. The third is an emergency medical technician and has experience in out-of-hospital emergency medical care. After independent rating, there were six disagreements, resolved through discussion. This rating task found 63 subreddits, called the `General Drug Dataset`. The top three subreddits by subscriber count were r/trees (1.2M subscribers as of September 2018), r/Drugs (446K), and r/Psychonaut (169K).

Gathering Subreddit Post Data. For the 63 subreddits, we gathered all text posts from Google's BigQuery, a data warehouse with publicly accessible, complete Reddit datasets [20]. Descriptive statistics of the `General Drug Dataset` are in Table 1. The number of posts per subreddit ranged from 5 to 793761, with a mean and median of 25381 and 984 posts/subreddit.

Unique subreddits	63		
Total posts	1,446,948	Post authors	429,447
Avg post len (words)	124.792	Mean post/user	2.12
Median post length	70.0	Median posts/user	1.0
Std. dev. post length	193.712	Std. Dev. posts/user	5.17

Table 1: Statistics of the `General Drug Dataset`

4 METHODS

Figure 1 presents a summary of our methods to address our two research questions, elaborated in the subsections below.

RQ1: Identifying OUD Recovery Behaviors

In RQ1, our goal is to identify posts in the `General Drug Dataset` that discuss OUD recovery. Manual annotation would provide high quality labels; however, because of time and data size (1.45M posts), manually annotating posts would also not scale to train a stable, robust classifier. In the absence of gold standard labels, we therefore adopted a binary supervised transfer learning approach for this problem.

Transfer learning is an approach in machine learning that trains a reliable supervised model on a *different* but related dataset. This technique can better learn holistic meanings and contexts than keyword dictionaries or regular expression matching alone, as shown in prior work to infer mental health states in social media [88, 84]. In our case, we trained on data broadly labeled on recovery status (called the "source"). We then used this model to "transfer," or label posts for recovery/non-recovery in the `General Drug Dataset` (the "target").

[3]https://www.reddit.com/subreddits/search/

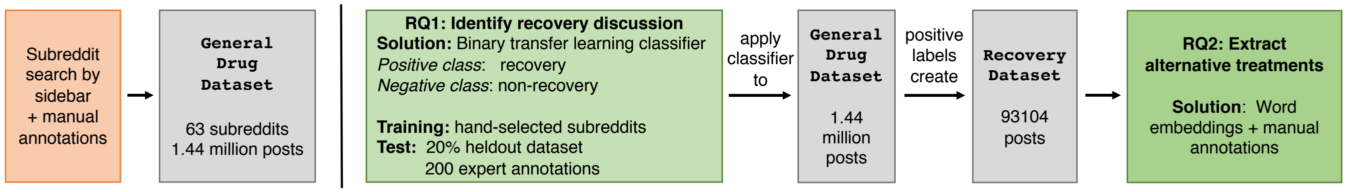

Figure 1: Flowchart of our research pipeline.

Transfer Learning Source Data. We used three precisely-identified subreddits as the source for recovery-labeled posts (positive examples): they included r/OpiatesRecovery, r/suboxone, and r/methadone. The subreddits were validated by the addiction research scientist as the strongest signal of OUD recovery from the `General Drug Dataset`. This dataset contains 16317 posts.

As negative examples, we used two types of posts: drug discussions and general Reddit discussions, offering diverse as well as complex examples. Specifically, drug discussions came from sampling posts from five subreddits: r/trees, r/Drugs, r/heroin, r/fentanyl, and r/Carfentanil. We sampled from r/trees and r/Drugs for drug discussion, and we pick three subreddits about opioid abuse to provide challenging examples of active use not connected to recovery. To represent general discussion on Reddit, we sampled from 100,000 posts from popular text subreddits on Reddit's homepage, including r/gaming, r/IAmA, and r/AskReddit, provided to us by the authors of [84]. We empirically found that optimal transfer performance peaked at 20000 negative posts and a 68%/32% drug discussion/popular split for the composition of class 0.

Classification Task. Our response variable is binary, indicating whether a post is about OUD recovery (1) or not (0). We preprocessed the data by lowercasing all words, and removed punctuation, stop words, URLs, and regular expression matches to "recover*" to prevent overfitting to explicit declarations of recovery. As features/predictor variables, we included term frequency-inverse document frequency (TF-IDF) uni-grams from the posts. We experimented with the inclusion of bi- and tri-grams and the number of features (between 100-20,000).

We built several classifiers interpretable for human exploration, including Logistic Regression, Support Vector Machine, and Random Forests, tested using both k-fold cross-validation(k=5) and on a held-out dataset (80/20 training/test split). Results are reported on the best classifier on the held-out datasets - a binary logistic regression (l2, C=0.1) with the top 10,000 uni-grams as features.

We applied our transfer learning classifier to machine label all 1.44M posts in the `General Drug Dataset`. Since the posts labeled recovery are of interest in RQ2, we call this the `Recovery Dataset`.

RQ2: Identifying Alternative Treatments in Recovery

Next, we examined the posts in the `Recovery Dataset` to identify ATs in OUD recovery and contextualize their use.

Word Embeddings. To identify potential ATs, we draw on the success of advances in deep learning and natural language processing with word embeddings [61]. Word embeddings learn complex, non-linear relationships in input text data by projecting words into a continuous vector space. In health informatics research, word embeddings have successfully identified drug slang [90] and contextually relevant health words [13, 101]. We used word2vec [61] to build custom word embeddings for our `Recovery Dataset`, adopting the continuous bag of words architecture and a minimum count of 50 to remove misspellings.

Disambiguating ATs. There are challenges in identifying ATs for OUD recovery from other uses of drugs. First, there is no resource of drugs, comprehensive or partial, to identify ATs for OUD recovery. Moreover, many drugs identified with a purely automated approach may identify drugs co-morbid with OUD recovery (prescribing an anti-nausea to counteract withdrawal symptoms) or polydrug use not connected to recovery (using cocaine and opioids, but not for recovery).

We devised a three step approach to validate our discovery of ATs. Using the results of the word embeddings, we condensed drug names and their equivalents/slang terms to a list of regular expressions referring to the same substance. After obtaining aggregated word frequencies of these drugs and their slang from the `Recovery Dataset`, we took the top 40 potential ATs, randomly selected 10 posts for each substance, and inspected to see if any posts indicate their use for OUD recovery.

5 RESULTS

RQ1: Transfer Learning Results

Evaluating Classifier Performance. We begin by presenting outcomes of the transfer learning classifier in Table 2. For the goodness of fit, compared to the `Null` model, our transfer learning model has a significant decrease in deviance, demonstrating that our model provides substantial explanatory power. The difference between the `Null` and the deviance of our transfer model approximately follows a X^2 distribution: X^2(9999, N=35634)=55104-22712=32392, $p < 10^{-15}$. On the 20% heldout data, our model achieved impressive

Model	Deviance	df	χ^2
Null	55104	0	
MODEL	22712	9999	32392
Actual/Predicted	Class 0	Class 1	Total
Class 0	4867	130	4997
Class 1	557	2674	3231
Accuracy	97.3%	82.7%	91.7% (mean)
Precision	0.90	0.95	0.92
Recall	0.97	0.83	0.92
F-1	0.93	0.89	0.92
AUC	0.901		

Table 2: Summary of model fit and performance of the transfer learning classifier on the 20% heldout dataset.

performance, at 91.7% accuracy and precision/recall/F1 of 0.92/0.92/0.92. In Figure 2, we report the receiver operating characteristic (ROC) curve, illustrating the false positive and true positive rate at various settings; the area under the curve (AUC) is 0.901.

We then ran this transfer learning classifier on the `General Drug Dataset` and took the posts marked class 1 (recovery) to generate the `Recovery Dataset`. The classifier identified 93,401 posts related to OUD recovery from 63 subreddits. We use these posts in RQ2.

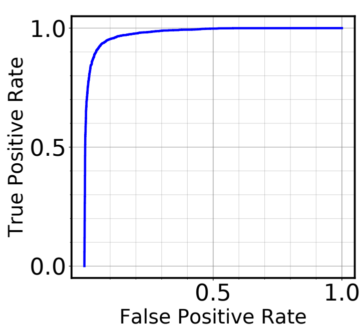

Figure 2: ROC curve for the transfer learning model.

Analysis of Top Predictors. In Table 3, we present 20 of the top 30 predictive independent variables/features with their β values and significance values from the logistic regression. Positive β values indicate that presence of the feature (n-gram token) in a post increases its likelihood of belonging to recovery (class 1), and negative β values from not recovery (class 0).

The variables most associated with recovery (class 1) are self-explanatory. This include words around opioids ("opiates," "heroin"), stopping use and symptoms ("clean," "sober," "withdrawal," "quit," "cravings," "relapse"), external resources to help with recovery ("rehab," "clinic," "na" (Narcotics Anonymous), "meetings"), as well as verified OUD recovery drugs ("methadone," "suboxone"/"sub"). In contrast, the words most associated with non-recovery and drug use include many kinds of drugs ("mdma"/"molly," "weed," "lsd," "adderall"), and continued use and research into the effects of drugs ("trip," "smoke," "took," "effects," "tolerance," "safe"). These results suggest that our transfer learning classifier is sensitive to behavioral signals of OUD recovery.

Feature	β		Feature	β	
clean	5.79	***	mdma	-2.46	***
suboxone	4.26	***	weed	-2.43	***
methadone	3.74	***	trip	-2.26	***
days	3.61	***	lsd	-2.12	***
addiction	3.23	***	smoke	-1.84	***
opiates	3.22	***	drugs	-1.70	***
heroin	2.79	***	adderall	-1.57	***
rehab	2.48	***	acid	-1.55	***
addict	2.37	***	shrooms	-1.48	***
sober	2.36	***	tolerance	-1.31	***
sub	2.36	***	effects	-1.26	***
clinic	2.19	***	dxm	-1.12	***
withdrawal	2.12	***	coke	-1.05	***
relapse	2.07	***	friend	-1.03	***
na	2.07	***	cocaine	-1.02	***
detox	1.98	***	dmt	-0.98	***
meeting	1.98	***	took	-0.96	***
quit	1.97	***	xanax	-0.96	***
meetings	1.94	***	molly	-0.94	***
cravings	1.84	***	safe	-0.90	***

Table 3: Selected features with the largest positive/negative coefficients (β) given by the transfer learning classifier. $p < 0.001^{***}$, adjusted using Bonferroni correction ($\alpha/10{,}000$)

Verification on Expert Labeled Data. Finally, we verify the performance of the transfer learning classifier on human-labeled data drawn from the `General Drug Dataset`. Two experts, the addiction research scientist and an expert on mental health and social media, annotated posts to assess whether the user was in recovery or advocated behaviors strongly correlated to recovery, like harm reduction or temporary cessation. The annotators used the Transtheoretical Model of Behavior Change [74, 73] as a clinically grounded method to analyze recovery, and correlated recovery signals recommended by the addiction research scientist [93].

First, the annotators labeled a sample of 200 posts from the `General Drug Dataset` and then adjusted their rating schema. Next, they independently and blindly rated another 200 labeled by the classifier, 100 from each class. On the final set of 200 posts, the interrater reliability (Cohen's κ) between the two raters was 0.83; the raters then mutually resolved disagreements. Compared to the ratings of the experts, the classifier performed at strong accuracy for transfer learning of 79%, with precision/recall/F1 of 0.81/0.79/0.79. Class-wise performance on the recovery class (class 1) was strong, with precision/recall/F1 of 0.70/0.85/0.77.

Error Analysis. We finish with an error analysis of the outcomes of the transfer learning classifier, focusing on its performance on the 100 expert-labeled recovery (Class 1) posts and the errors the classifier made.

We start with an example of a *true positive*, a post where the classifier($P(\text{Class}_1) = 0.664$) and human ratings agreed.

> It's day 4 of being clean...sleeping is so-so, sweating like crazy. I had bad restless legs until midnight, melatonin is really helping me. Today is way better than yesterday. *(r/OpiatesRecovery)*

The author of this post is looking for support through the initial stages of withdrawal from heroin misuse, and the classifier was able to correctly identify this.

We move to *false positives*, or posts incorrectly marked as recovery by the classifier but annotated not recovery by human raters.

One category of *false positives* was semantic ambiguity of "clean" ($P(\text{Class}_1) = 0.601$).

> I have a glass bong, and I'm out of my normal cleaning mix. If i ran some windex first in it, is it a good or bad idea to clean it? (*r/trees*)

"Clean" for OUD recovery refers to sobriety, but the classifier often identified when clean referred to the act of cleaning pipes, bongs, and drug paraphernalia. Because the classifier uses uni-grams as input, it cannot disambiguate between these two meanings.

Another example of *false positives* include expressions of sadness or suicidal thoughts, but no intention to recover from OUD ($P(\text{Class}_1) = 0.805$):

> I've used everyday for the past 4 years, besides jail and moving. I'd be better off in jail, or even better, dead. I don't have anything left in the world...I don't think I could ever quit. (*r/opiates*)

Although this post suggests discontent about OUD, the author makes no indication that they are moving towards recovery or changing their substance use patterns. This means that they are not moving into the pre-contemplative phase of the Transtheoretical Model [74]—the rationale for why the experts labeled the post as non-recovery.

RQ2: Identifying ATs with Word Embeddings

Next, we discuss our word embedding analysis of 93,104 recovery posts to identity ATs for OUD recovery. Table 4 presents the outcomes of this word embedding analysis, containing 1,019,459 unique tokens. For each, we show the 20 most similar tokens in the embedding, based on cosine similarity. Cosine similarity measures the similarity of the angle between two vectors and ranges from -1 (semantically absolute opposites) to 1 (identical)

To begin identifying ATs, the addiction research scientist identified four kinds of substances related to OUD recovery: those grounded in clinical recovery (methadone, suboxone) or known ATs (kratom, iboga); medications commonly encouraged for opioid recovery (phenibut, Imodium); opioids of abuse (fentanyl, heroin); and finally, drugs with interactions with opioids (gabapentin, pregabalin), presented in Table 4.

In the tokens identified by word embeddings, we identify additional opioids and drugs of abuse, such as oxycodone, acetyl, and opium. The word embeddings also include slang for OUD recovery drugs ("mmt," "sub"), and mentions of benadryl, often used during withdrawal to reduce nausea. However, we also identify categories of drugs not directly associated with OUD recovery, such as benzodiazepines, and other drugs of abuse such as cocaine and methamphetamine.

To disambiguate what drugs are related to AT use rather than polydrug or other co-morbid drug use (ref. Methods), recall we identified the most frequently discussed drugs extracted from the word embeddings in the `Recovery Dataset`. To verify these drugs are ATs, we randomly sampled 10 posts from the dataset that contain the drug names and then manually inspected the content. If at least one post suggests the user is using the substance as an AT, we consider that substance a potential AT. One rater, a social computing expert with expertise in mental health and recovery, completed this annotation task, with consultation from the addiction research scientist.

We present the top 20 potential ATs identified by the rater in Table 5—this preliminary list is the first list of potential ATs for OUD recovery. We contextualize AT use and effectiveness for OUD recovery by exploring representative quotes (post excerpts) from our `Recovery Dataset` that contain these drug names.

First, we notice the use of benzodiazipines (xanax, klonopin, valium, clonazepam, diazepam, clonazolam):

> I went to a doctor and have **xanax**, subs, immodium, etc to ride out the withdrawal. After three days of detox...no withdrawals...(*r/OpiatesRecovery*)

Benzodiazepines can be useful drugs to manage anxiety and insomnia [42]; however, these drugs bear risks when used in OUD recovery. First, benzodiazepines are a depressant and when mixed with opioids, can increase the risk for overdose [44, 18]. Second, benzodiazepines have high risk for misuse, and withdrawals can be life-threatening [42]. We see this concern echoed in the dataset:

> But over the last week or two I've had to use **temazapam** to sleep at all...I wish that I hadn't underestimated how bad withdrawals get after the first few days; I wouldn't have taken so many **benzos**. I'm afraid I'll swap one addiction for another. (*r/quittingkratom*)

Users report being afraid of the risks of benzodiazepines, either replacing their OUD with another substance or becoming dependent on both opioids and benzodiazepines.

Next, we move to a known AT: kratom. On one hand, many users report success tapering off opioids like heroin and fentanyl, and how it assists with withdrawal symptoms:

> I took an unconventional approach to getting clean, using **kratom** and LSD...I used the kratom to taper off heroin and the LSD to relax me...It's been two months and I'm still clean. (*r/opiates*)

On the other hand, there are many users who report that they start misusing kratom as a replacement for opioids during self-managed OUD recovery:

Word	Drug-Related Words from Embedding
fentanyl	fent (0.83), morphine (0.77), codeine (0.75), hydromorphone (0.74), oxymorphone (0.72), 50mcg (0.71), heroin (0.7), dilaudid (0.7), hydromorph (0.7), oxycodone (0.7), acetyl (0.69), ketamine (0.69), oxycontin (0.69), h (0.68), dihydrocodeine (0.68), diluadid (0.67), methamphetamine (0.67), heroine (0.67), intranasal (0.67), herion (0.66)
heroin	meth (0.87), h (0.82), heroine (0.81), herion (0.79), cocaine (0.75), fentanyl (0.7), opiates (0.68), methamphetamine (0.66), coke (0.66), dope (0.64), bth (0.64), pot (0.64), marijuana (0.62), polydrug (0.62), fent (0.61), opium (0.61), k (0.61), weed (0.61), crack (0.61), opiate (0.6)
suboxone	subutex (0.92), methadone (0.91), subs (0.84), bupe (0.81), buprenorphine (0.78), zubsolv (0.76), suboxen (0.74), naltrexone (0.72), mmt (0.7), suboxonesubutex (0.68), bup (0.68), kratom (0.68), klonopin (0.67), clonazepam (0.66), diclazepam (0.65), tramadol (0.64), zoloft (0.63), etizolam (0.63), vivitrol (0.63), trams (0.62)
methadone	suboxone (0.91), subutex (0.85), bupe (0.79), buprenorphine (0.77), subs (0.73), mmt (0.73), zubsolv (0.71), bup (0.69), suboxen (0.69), naltrexone (0.68), suboxonesubutex (0.65), maintenance (0.63), diclazepam (0.63), vivitrol (0.61), tramadol (0.61), mdone (0.61), zoloft (0.61), klonopin (0.61), diazepam (0.6), clonazepam (0.6)
phenibut	tianeptine (0.85), etizolam (0.85), loperamide (0.85), lope (0.84), clonazolam (0.82), dxm (0.8), etiz (0.79), lyrica (0.79), pst (0.79), gabapentin (0.79), pregabalin (0.78), immodium (0.78), imodium (0.77), diclazepam (0.76), xanax (0.76), mxe (0.76), modafinil (0.76), baclofen (0.75), valium (0.75), clam (0.75)
bup	buprenorphine (0.78), zubsolv (0.72), bupe (0.71), methadone (0.69), suboxone/subutex (0.69), suboxone (0.68), subutex (0.67), methadose (0.67), suboxone/methadone (0.66), naltrexone (0.66), nucynta (0.66), naloxone (0.66), memantine (0.65), flunitrazepam (0.64), methodone (0.64), sublingual (0.64), 1mcg (0.63), subxone (0.63), uld (0.62), suboxen (0.62)
loperamide	lope (0.87), imodium (0.87), immodium (0.87), phenibut (0.85), agmatine (0.82), pregabalin (0.81), gabapentin (0.81), tianeptine (0.8), lyrica (0.79), diclazepam (0.77), 5htp (0.77), clonidine (0.77), niacin (0.77), modafinil (0.76), bso (0.76), etizolam (0.75), baclofen (0.75), neurontin (0.74), dlpa (0.74), clonazolam (0.74)
lope	loperamide (0.87), phenibut (0.84), immodium (0.83), imodium (0.82), gabapentin (0.8), diclazepam (0.77), etizolam (0.77), clonidine (0.76), 5htp (0.76), etiz (0.75), trams (0.75), clam (0.74), agmatine (0.74), lyrica (0.74), clonazolam (0.73), niacin (0.73), sampv (0.72), melatonin (0.72), tianeptine (0.71), benadryl (0.71)
pregabalin	lyrica (0.87), baclofen (0.87), clonodine (0.85), promethazine (0.85), gabapentin (0.84), hydroxyzine (0.84), neurontin (0.83), mirtazapine (0.81), immodium (0.81), imodium (0.81), clonidine (0.81), loperamide (0.81), diphenhydramine (0.81), lorazepam (0.8), seroquel (0.8), dxm (0.8), tizanidine (0.8), tianeptine (0.8), remeron (0.78), modafinil (0.78)
gabapentin	clonidine (0.92), lyrica (0.91), neurontin (0.89), clonodine (0.87), seroquel (0.87), valium (0.85), pregabalin (0.84), hydroxyzine (0.84), immodium (0.83), imodium (0.83), baclofen (0.82), lorazepam (0.81), klonopin (0.81), temazepam (0.81), loperamide (0.81), clonazepam (0.8), lope (0.8), ativan (0.79), trazadone (0.79), xanax (0.79)
iboga	ayahuasca (0.72), ibogaine (0.72), experimental (0.63), assessment (0.63), np (0.62), evolution (0.62), unconventional (0.61), comprehensive (0.61), aftercare (0.6), detoxification (0.59), fundamental (0.59), accelerated (0.59), psychiatry (0.59), author (0.58), ancient (0.58), article (0.58), error (0.58), unbiased (0.58), incarceration (0.58), agent (0.58)
kratom	cannabis (0.75), k (0.75), opiates (0.72), phenibut (0.7), tramadol (0.7), pst (0.68), suboxone (0.68), marijuana (0.67), loperamide (0.67), mj (0.67), etizolam (0.66), trees (0.66), weed (0.66), tianeptine (0.65), h (0.65), lope (0.64), opis (0.64), bupe (0.63), subutex (0.63), subs (0.63)

Table 4: Top 20 word embedding tokens most similar to tokens identified by the addiction research scientist. Numbers in parentheses represent the cosine similarity value between the tokens.

Drug	Count	Drug	Count	Drug	Count
kratom	8526	clonidine	643	seroquel	137
loperamide	3399	ativan	404	tianeptine	136
xanax	2082	clonazepam	364	agmatine	123
valium	875	magnesium	359	dxm	118
klonopin	847	lyrica	199	iboga	114
gabapentin	803	theanine	151	niacin	91
etizolam	714	clonazolam	147		

Table 5: Top 20 potential ATs derived from our word embeddings analysis. Count represents the occurrences in the `Recovery Dataset`.

> I am finally ready to get rid of a burden that once was a blessing...**Kratom**. I take **kratom** everyday so I don't go through withdrawals. (*r/quittingkratom*)

We note that there was even a subreddit created to facilitate recovery from kratom in our dataset, r/quittingkratom.

Others describe their difficulties in reducing use of kratom and comparisons to other kinds of opioid withdrawal:

> I went thro every kind of opioid withdrawal imaginable - for me, **kratom** withdrawal was by far worse than any H[heroin] withdrawal I ever did. (*r/OpiatesRecovery*)

This replicates findings in the clinical literature around OUD recovery facilitated by kratom [9]: kratom's use as an AT has unclear and controversial effectiveness.

Next, we turn to Imodium, an over-the-counter medicine commonly prescribed to manage diarrhea, a symptom of opioid withdrawal. We were surprised to see it being referred to as "lope," short for loperamide, as Imodium had acquired a slang name.

We found that Imodium was being used as an AT prone to misuse and dependence:

> Switched from suboxone and opioids to **lope**. I take one bottle of 72 for every twelve hours, and I get a slight opiate high when I take it...I've been doing this a year now, now I want to quit it. (*r/opiates*)

These complaints were frequent enough that one user wrote an extensive post discussing how to use Imodium to taper effectively without becoming dependent:

> Treat **loperamide** like Suboxone - it's an opioid replacement and has a bad withdrawal and a long half life. You're fooling yourself if you think using Imodium to 'take the edge off' isn't extending your WDs [withdrawals]. (*r/OpiatesRecovery*)

Most medical resources regard Imodium as a well-tolerated drug, and only one study from 1980 suggests it may be misused during OUD [41]. We find indication that users are reporting Imodium as an AT with unclear effectiveness.

Finally, we notice the trend of users creating "stacks" or "kits" of many substances as a comprehensive AT for OUD recovery. These users elaborately combine prescription drugs, illicit drugs, over the counter medications, vitamins/minerals, and other substances to ameliorate withdrawal symptoms:

> I've decided to quit for good - what you guys think about my withdrawal strategy?...got lots of **clonazepam**, **xanax**, **cannabis**, and **lope**, a 6 pack of some IPAs [beer], and **nyquil**. (*r/opiates*)

The user then describes the specific dosing patterns and timings of using these medications to alleviate withdrawal and start OUD recovery.

Other users report combining substances all at once to help with withdrawal symptoms.

> Over 8 hours I took 4 **muscle relaxers**, my dose of **ropinirole**, 800mg of **advil**, **magnesium**, **niacin** [a B vitamin]...and **St John's Wort**. (*r/OpiatesRecovery*)

Mixing drugs poses unintended interaction and could amplify overdose if relapse occurs.

To summarize, in RQ2 we used word embeddings and human annotation to identify a first list of potential ATs in OUD recovery. Our analysis reveals that many of these ATs have mixed effectiveness: users report both successes and risks with their usage in regards to OUD recovery and managing withdrawal.

6 DISCUSSION

Health Implications and Harm Reduction

Our research provides a major step in improving knowledge of ATs in OUD recovery. The outcomes of our word embeddings analysis in RQ2 offered an initial list of drugs being used as ATs, which has the potential to influence OUD research and treatment.

Promoting Research. The information we discovered in RQ2 can be useful for researchers investigating new substances used for OUD. For example, we discovered that Imodium was being used as an AT on Reddit. This surprised us, as the most recent study on this interaction was from 1980 [41]. In addition to guiding new treatment research, future work using techniques like ours could guide new explorations into dosing and treatment protocols, mirroring prior work in the space [32]. Especially for ATs that have mixed effectiveness, scientific inquiry is urgently needed to support policy decisions around these substances [34].

Behavioral Health. Our results may also provide benefits to behavioral health clinicians to deliver safer and more effective care for substance use disorders. With patient consent to share data from social media, we envision the recovery classifier from RQ1 can provide collateral insights to clinicians to understand precipitants of negative outcomes in their patients. The list of ATs found in RQ2 also gives clinicians new information when soliciting prior patient history. In RQ2, we found that benzodiazepines were being used to facilitate recovery, something important for behavioral health clinicians to know when facilitating positive behavior change. Finally, the discovery of new ATs and resulting scientific exploration could help clinicians better manage dosing protocols to design more effective treatment practices.

Harm Reduction. Broadly, we see this work as encouraging the larger, social goal of *harm reduction* with addiction, OUD management, and recovery efforts. Harm reduction consists of policies and attitudes to minimize the risks of dangerous drug use behaviors [58]. Although harm reduction efforts have seen great success in needle exchange programs for injectable drug use [55], responses to ATs for opioids have been mixed. The US Food and Drug Administration has considered criminalizing the sale, use, and research on kratom by moving it to Schedule 1 status [34].

We discovered that users report dependence on ATs, and in some cases interactions between ATs can be very dangerous. Therefore, we do not endorse these ATs given the medical and physiological risks. However, these users are attempting to reduce the harm of dependence on opioids, *even if these approaches are clinically unverified or potentially dangerous.* These behaviors represent efforts at harm reduction. Recognizing, rather than eschewing, these behaviors is an important step to promote safer drug use among OUD patients. Invalidating the attempts we discover in this paper – at what could be positive recovery strategies for some individuals– could add to existing marginalization and stigma and lead patients to dismiss medical treatments as close-minded Western medicine. We encourage clinicians, therapists, and those involved in OUD recovery efforts to reconsider how patients are using ATs in light of our findings and consider how to incorporate these insights into new investigations.

Stigma & Designing Interventions for Addiction

Any intervention in OUD recovery is complicated by *stigma*, a term Goffman defines as an attribute that makes an individual undesirable, tainted, or socially unworthy [36]. Being labeled an "opioid addict" is highly stigmatizing – OUD patients are perceived as having more control over their disease, inciting blame and discrediting their need for medical help [54]. Indeed, most societies look down on addicts, criminalizing their behavior and shunning them from societal participation. Stigma in OUD leads to many negative consequences, including hiding or concealing behaviors, lack of social support, reluctance to enter recovery treatment, and poor treatment outcomes [67, 53]. Even attempting recovery is stigmatized — despite clinical success, participants in methadone maintenance therapies are frequently reduced to "dope addicts" or "junkies" [5, 21].

Pseudonymous and anonymous social media platforms provide a unique opportunity for individuals struggling with stigmatizing conditions to connect and find support, a topic of current interest in HCI [3, 2, 57, 82, 83]. We build on this work and offer several considerations for understanding and engaging with stigmatizing behaviors like OUD and addiction in online communities.

Understanding Online Communities. We see the methods in this paper as a valuable contribution to understanding stigmatizing behaviors in online communities. In RQ1, we implemented a transfer learning approach to robustly detect recovery behaviors when no gold standard labels exist in online communities. This is useful for other quantitative approaches for analyzing online communities to bootstrap ground truth labels in difficult contexts. Our human-in-the-loop approach, which combined word embeddings and manual annotation (RQ2), extracted novel terminology related to AT use, a technique that can be flexibly adopted for identifying new language emergence patterns or terminology in online communities.

Intervention Design and its Challenges. More important to online communities is how to best design interventions that might support harm reduction techniques or promote behavior change with OUD and addiction.

Our approach could broadly be used to facilitate better health decisions by those suffering from OUD. In RQ1, we designed a transfer learning classifier that could separate recovery behaviors from non-recovery behaviors. With further improvement of the classifier and expert input, we envision intervention strategies based on classification output. New community tools could be deployed for Reddit if a user is identified as posting a recovery post. This could be implemented in support matching techniques to other users who have been successful in OUD recovery. Tools could also provide advice to the user, like how to safely managing withdrawal symptoms. Combining the insights about ATs from RQ2, we see potential for campaigns to promote harm reduction or promote healthier behaviors in those struggling with addition. For example, public service announcements, interstitials, or advertisements could contain information about the safe use of certain ATs or drug combinations to avoid (such as mixing benzodiazepines and opioids), guiding users to make better choices even if not in active recovery.

However, these technological interventions must be designed with stigma at the forefront of consideration. Providing dignity and respect to OUD sufferers is essential to promoting better outcomes - yet many questions emerge when designing technological interventions for OUD. At what point is intervention appropriate for a person, and how do we assess that? Do targeted interventions diminish the agency and respect of individuals who suffer from OUD? Who is obligated to intervene in cases of AT use that are dangerous and potentially life-threatening? Is encouraging certain ATs dangerous enough to warrant removal or banning content from platforms?

In particular, social media platforms have both the ability to support stigmatized communities for seeking healthy behaviors [56, 3] *and* marginalize with intervention strategies [13]. Prior work in HCI is decidedly mixed on the effectiveness of platforms to manage stigmatizing and deviant behavior. Research has shown that banning strategies were successful in pushing abusive behavior off Reddit [17]. However, efforts at curbing deviant *mental health behaviors* have had negative effects on health and community dynamics [16].

Whether using ATs in OUD recovery is a "deviant" recovery behavior that requires intervention is a contentious issue with no easy answers. However, given the marginalization of individuals adopting ATs and who have OUD broadly [100], any form of platform- or community-wide intervention policy must carefully balance the trade-off between curbing dangerous health behaviors and providing marginalized individuals with a "safety valve" through self-disclosure [27]. Platforms face challenges balancing community needs, social responsibility, and corporate goals in designing interventions for promoting or discouraging these behaviors. We hope that interventions would be crafted to promote better health outcomes as well as respect the agency of those with OUD.

Through our findings and this discussion, we hope to encourage computational researchers, designers, and social networks to design technically sound, ethically rigorous, and compassionate intervention strategies for stigmatizing conditions and experiences like OUD.

Ethics and Substance Use Research in HCI

As highlighted in the Related Work section, research work in substance use and recovery, illicit or otherwise, has been of recent interest to HCI, seen in panels [46], Yarosh's work with colleagues [83, 81, 87] and Maclean et al's investigation on prescription drug abuse recovery forums [56]. Given this growing interest and the sensitivities of studying vulnerable populations, attention to ethical challenges is paramount.

Managing Risk Without Oversight. In our dataset, Reddit users *publicly* discuss sourcing, selling, and using a variety of substances. The coverage of such research by ethics review boards is unclear. Many institutions do not require ethics board approval for publicly accessible data with no interactions from researchers; indeed, our institutions do not require approval on public social media research.

A lack of ethics board approval, however, does not indicate a lack of risk in the research. Aggregating and analyzing data transforms its initial purpose, and the presence of aggregated datasets could lead to reidentification of participants. Once identified as an opioid addict, individuals could suffer harm to reputation, employment, as well as criminal investigation.

In this research, we deliberately took steps to protect participants from these risks. By working with an addiction research scientist at every step, we incorporated their unique insights about addiction, stigma, and recovery as well as ethically ground our findings in the substance use literature. We obtained a certificate of confidentiality issued by the National Institutes of Health to prevent our data and analysis from forced disclosure, including by government authorities. We adopted computational and manual curation techniques to deidentify data, including deidentifying users and locations, securing data behind firewalled servers, and only downloading subsamples of data to local machines. Further, quotes were lightly edited in the paper to prevent reidentification of participants, highlighted in recent research as an important ethical practice [7].

Bad Actors. Beyond ethical considerations and best practices, researchers must also confront the *responsibilities* of their work. This includes risks from deidentification and from data analysis and insights in real-world scenarios.

One risk is the misuse of algorithmic output for purposes other than those directly beneficial to participants in these communities. Benevolent actors intending to assist sufferers can inadvertently cause harm, as was seen in the case of Samaritan's Radar app [68]. The app scanned Twitter for key phrases, then informed users when their Twitter contacts were potentially in need of emotional support. Although the charity had the right intentions – instrumenting social media activity for suicide prevention – critics identified multiple issues with deployment, ranging from privacy and consent concerns to enabling stalkers and bullies to target victims when they were most vulnerable [30].

Additional risks surface when these algorithms are used for unsavory and nefarious purposes. OUD is a complex disease, yet its stigma causes consequences for getting treatment. We worry that health care companies could use this research to identify those using ATs and deny coverage. There are also actors whose intentions are more complex. Police departments and law enforcement agencies could develop monitoring systems to surveil new ATs, identify particularly risky ATs for risk of overdose, and take measures to remove them from the market to prevent harm. On the other hand, triangulation of this data with other datasets could re-identify individuals and risk criminal investigation or arrest.

Consequently, researchers must take responsibility for work that may cause known and unknown harms, a provocative stance argued by ACM's Future of Computing Academy [40]. We encourage data scientists and quantitative researchers to consider risks to participants and other stakeholders when examining new areas of sensitive research.

Limitations and Future Work

We note some limitations in this research. First, self-selection influences disclosure of OUD recovery behaviors and use of ATs. There are likely population biases of who discloses on public social media that they use ATs. We also expect positive survivorship bias in our dataset, oversampling those who continue using Reddit – we cannot identify the reasons why people stop using online communities to discuss ATs. This is complicated by issues of deviance and stigma within AT use and OUD. We also deliberately adopted a broad definition of recovery to develop our recovery transfer learning classifier in RQ1. This included behaviors seen in the Transtheoretical Model of Behavior Change [74] and harm reduction behaviors [93]. We did not have labels on whether individuals actually were in recovery at the time of their posts. We caution against using our work to build individual-level predictions of clinical recovery status in OUD communities. Our methods are used at the aggregated level to identify potential ATs reported by these communities.

Future Work. We are excited at future work which may use our insights for improving health research. Clinical research could use our insights as springboards for future research to inform better medicine, addiction treatment, and policy. In line with the contributions provided by Frost et al [32], we see our work prompting new investigations into online communities to understand AT use. There is promising future work in analyzing the mechanisms and effectiveness of the individual ATs we list in RQ2, dosing strategies, practices of AT use, and other strategies of those using ATs in OUD recovery. This could involve data analysis of recovery trajectories, complementing prior work [56, 15].

Mixed methods and qualitative research methods, such as ethnographic and interview studies, would also provide rich context and important insights into OUD use and ATs. With patient consent, future work could supplement online social media posts with clinically validated assessments and insights into the recovery process. Domain expertise and collaborations with clinicians and relevant stakeholders will supplement this work and assist in understanding AT use for OUD on social media.

Finally, we see future work unpacking the complexities of addiction and its presentation in online platforms. By examining stigmatizing behaviors and disclosure on online platforms about OUD and AT use, we see this work furthering work on stigma and disclosure in online communities [3]. We also envision new technologies that can facilitate healthy recovery trajectories in the face of stigma.

7 CONCLUSION

We provided a large-scale analysis of alternative therapies for OUD recovery on Reddit. Collaborating with an addiction research scientist, we developed a transfer learning classifier that classifies recovery-related posts with 79% accuracy, and identified over 93,000 recovery-related posts. We then identified potential ATs used in OUD recovery using a hybrid deep learning and human annotation approach. Finally, we presented a qualitative contextualization of the use of ATs and potential effectiveness. This paper provides important benefits to clinical researchers, designers, and HCI researchers interested in a complex and stigmatized area like OUD.

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