Detecting risk level in individuals misusing fentanyl utilizing posts from an online community on Reddit

Sanjana Garg
Jordan Taylor
Mai El Sherief
Erin Kasson
Talayeh Aledavood

See next page for additional authors
Authors
Sanjana Garg, Jordan Taylor, Mai El Sherief, Erin Kasson, Talayeh Aledavood, Raven Riordan, Nina Kaiser, Patricia Cavazos-Rehg, and Munmun De Choudhury
Detecting risk level in individuals misusing fentanyl utilizing posts from an online community on Reddit

Sanjana Garg a,1, Jordan Taylor a,1, Mai El Sherief a, Erin Kasson b, Talayeh Aledavood c, Raven Riordan b, Nina Kaiser b, Patricia Cavazos-Rehg b, Munnum De Choudhury a,∗

a College of Computing, Georgia Institute of Technology, Atlanta, GA 30332, United States of America
b Department of Psychiatry, Washington University School of Medicine, St. Louis, MO 63130, United States of America
c Department of Computer Science, Aalto University, Espoo, Finland

ARTICLE INFO

Keywords:
Fentanyl
Opioids
Overdose
Machine learning
Detection
Social media

ABSTRACT

Introduction: Opioid misuse is a public health crisis in the US, and misuse of synthetic opioids such as fentanyl have driven the most recent waves of opioid-related deaths. Because those who misuse fentanyl are often a hidden and high-risk group, innovative methods for identifying individuals at risk for fentanyl misuse are needed. Machine learning has been used in the past to investigate discussions surrounding substance use on Reddit, and this study leverages similar techniques to identify risky content from discussions of fentanyl on this platform.

Methods: A codebook was developed by clinical domain experts with 12 categories indicative of fentanyl misuse risk, and this was used to manually label 391 Reddit posts and comments. Using this data, we built machine learning classification models to identify fentanyl risk.

Results: Our machine learning risk model was able to detect posts or comments labeled as risky by our clinical experts with 76% accuracy and 76% sensitivity. Furthermore, we provide a vocabulary of community-specific, colloquial words for fentanyl and its analogues.

Discussion: This study uses an interdisciplinary approach leveraging machine learning techniques and clinical domain expertise to automatically detect risky discourse, which may elicit and benefit from timely intervention. Moreover, our vocabulary of online terms for fentanyl and its analogues expands our understanding of online “street” nomenclature for opiates. Through an improved understanding of substance misuse risk factors, these findings allow for identification of risk concepts among those misusing fentanyl to inform outreach and intervention strategies tailored to this at-risk group.

1. Introduction

Amidst the opioid epidemic (Gostin et al., 2017), synthetic opioid misuse in particular has become an urgent public health crisis since 2013 when these illicitly manufactured synthetics started to become more readily available (DEA, 2015; DEA, 2018), contributing to nearly 12 times the number of overdose related deaths in 2019 than in 2013 (CDC, 2019). Fentanyl is a synthetic opioid that in particular is considered a serious threat (Springer et al., 2019), as it has driven the most recent wave of synthetic opioid deaths (Spencer et al., 2019; CDC, 2018). In 2016, fentanyl became the drug most frequently mentioned in relation to overdose deaths in the United States, surpassing heroin (Hedegaard et al., 2018). It is a highly potent drug, making it incredibly easy for users to become addicted as well as users of other drugs to unintentionally overdose on it, and it is often laced into substances without user’s knowledge, making risk for overdose much higher (Jones et al., 2018; NIDA, 2019). In fact, a study found that 73% of the participants who tested positive for fentanyl did not report fentanyl misuse, suggesting that they unknowingly injected or consumed the drug (LaRue et al., 2019; Amlani et al., 2015).

Many instances of overdose and harm related to fentanyl use in the United States are unintentional, often related to use of heroin, cocaine, and other drugs which are laced with fentanyl to increase their euphoric effects (CDC, 2021; NIDA, 2019). With regard to individuals who engage...
in intentional fentanyl misuse, however, theories about motivations for misuse include a high tolerance for other drugs including opioids that requires a more potent drug such as fentanyl to maintain a high, motivations related to addiction/dependence and misuse to reduce or mitigate withdrawal symptoms, or addiction resulting from accidental exposure to fentanyl (Buresh et al., 2019). Understanding motivations for and risks related to patterns of intentional fentanyl misuse via firsthand experiences is crucial to better adapt prevention and intervention strategies effectively. Yet, due to the illegal nature and stigma surrounding drug misuse, populations of illicit drug users are often difficult to reach. Research into motivations for illicit drug misuse also reflects a dynamic relationship between feelings of separation or isolation from others (i.e., social pain) as well as physical pain, and such pain may encourage cyclical, continued misuse of substances to reduce these feelings (Eisenberger, 2012; Sullivan and Ballantyne, 2021). Fentanyl misuse in particular is highly stigmatized; sufferers are often known to feel reticent to share their experiences with clinicians, researchers, and even family and friends (Nelson and Perrone, 2012). Consequently, for those labeled an "addict," this stigma causes many negative outcomes, including shame, embarrassment and unwillingness to enter treatment (Livingston et al., 2012). This makes it difficult to gather data to understand practices and risk factors surrounding fentanyl misuse through interviews or patient disclosures.

Pseudonymous social media sites can empower those with stigmatized identities to disclose experiences and seek support with diminished fear of offline harm (Andalibi et al., 2016). As such, pseudonymous social media has been used to study stigmatized experiences in the domains of LGBTQ+ minority stress (Saha et al., 2019), sexual abuse (Andalibi et al., 2016), parenting (Ammari et al., 2019), and mental health (De Choudhury and Sophovan, 2014; Pavalananthan and De Choudhury, 2015; De Choudhury et al., 2016; Naslund et al., 2016; De Choudhury and Kiciman, 2017; Andalibi et al., 2017; Cavazos-Rehg et al., 2017; Guntuku et al., 2017; Paul and Dredze, 2017; Coppersmith et al., 2018). One widely used pseudonymous social media site is Reddit, which offers topic-specific forums, known as subreddits, where users can vote and comment on each other’s posts anonymously, empowering users to discuss stigmatized topics (Singer et al., 2014; Betton et al., 2015; Andalibi et al., 2016; De Choudhury et al., 2016; Robinson et al., 2019). According to a Pew survey, in America, Reddit is used by about 15% of adult men, 8% of adult women, 22% of those ages 18 to 29, and 14% of those ages 30 to 49 (Perrin and Anderson, 2019). In the same survey, 14%, 12%, and 4% of Hispanic, White, and Black Americans respectively and 9%, 10%, and 15% of those with annual incomes less than $30,000, $30,000 to $74,999, and greater than $75,000 respectively reported using Reddit. Previous studies have used machine learning and natural language processing methods to analyze Reddit posts regarding casual drug discussions, opioid addiction, and alternative treatments for opioid use recovery (Park and Conway, 2018; Chancellor et al., 2019; Lu et al., 2019; Alambo et al., 2021). However, no known studies focus on fentanyl discussions in particular. Further, to our knowledge, none of the existing data and language analytic studies have focused on identifying or understanding specific risky behaviors associated with fentanyl misuse.

In response, the present study examines the content in the social media platform Reddit, specifically within the subreddit r/fentanyl. We use posts and comments from the r/fentanyl subreddit to assess fentanyl misuse risk factors using a mixed methods approach — first by developing a codebook using qualitative content analysis on the forum, and then building and validating supervised machine learning classifiers to detect risk. By identifying risk associated with intentional fentanyl misuse from social media, this work improves understanding of this substance for better clinical research, treatment and interventions, and outreach to populations which may be difficult to reach via conventional means.

2. Methods

2.1. Social media data

We collected public data from the subreddit r/fentanyl. The r/fentanyl forum describes itself as dedicated to harm reduction and the exchange of information about fentanyl and its analogues that offers firsthand user experiences and advice with the goal “to dispel some common myths about these substances.” We collected all posts and comments (content) from the beginning of the subreddit’s history in May of 2015 to January 2020 using PRAW library (Boe, 2016) and Google Big Query (BigQuery, 2019). Our dataset from r/fentanyl is summarized in Table 1; it includes 6459 posts and comments from 1124 unique users. However, as can be seen in Table 2 120 posts and 361 comments were written by users who later deleted their account, so the number of authors in our dataset is likely larger than 1124.

Since these data were collected from the publicly available subreddit r/fentanyl, this study does not constitute human subjects research and was not subject to institutional review. To protect user identities, we have not included usernames, nor direct quotes; also, example quotes are paraphrased to reduce traceability.

To help with the automated detection of fentanyl misuse on this Reddit forum, we first identified posts and comments that were first-person reports of fentanyl use; this is important because these communities harbor a variety of content ranging from attitudes about fentanyl use, personal experiences, news and misinformation, side-effects of use, as well as experiences about relapse and abstinence. For this, we employed a machine learning classifier developed on the annotated medication intake Twitter dataset by Klein et al. (2017). This classifier classifies posts into two categories: intake (self-reported) and no-intake. Using this classifier in a transfer learning setting (Howard et al., 2020), a total of 1628 posts and comments in our initial dataset of 6459 were identified to be about first-hand self-reports of fentanyl intake (Table 1). We used this classifier to select a 60% intake 40% no-intake content split on r/fentanyl for 391 annotated posts or comments. We chose to include data classified as no-intake because our codebook contained categories not associated with drug intake, such as discussing withdrawal, tolerance, or color. As can be seen in Table 2, the distribution of posts and comments from deleted users in our annotated dataset is comparable to the proportion of posts and comments with text from deleted users in our entire dataset. We can also see in Table 3 that while most users only have one post or comment in our annotated dataset, these users tend to be more frequent posters or commenters than the median user. This is to be expected because the number of posts and comments per user follows a power law distribution.

Table 1 Data description from r/fentanyl.

<table>
<thead>
<tr>
<th></th>
<th>#</th>
<th># users</th>
<th>avg. words</th>
<th>intake</th>
<th>no-intake</th>
</tr>
</thead>
<tbody>
<tr>
<td>Posts</td>
<td>804</td>
<td>422</td>
<td>88</td>
<td>207</td>
<td>597</td>
</tr>
<tr>
<td>Comments</td>
<td>5655</td>
<td>980</td>
<td>54</td>
<td>1421</td>
<td>4234</td>
</tr>
<tr>
<td>Total</td>
<td>6459</td>
<td>1124</td>
<td>59</td>
<td>1628</td>
<td>4831</td>
</tr>
</tbody>
</table>

2 PRAW (“Python Reddit API Wrapper”) is a Python package that provides an interface to scrape data from Reddit using Reddit’s API.

3 Google BigQuery is a platform that enables analysis over big data of the order of petabytes. Along With that, it also contains Reddit posts and comments from different subreddits stored as datasets. We used Google BigQuery only for retrieving data and not for analysis.
The performance of our risk models is summarized in Table 5 and includes the mean precision, recall, F1, accuracy and AUC across each fold corresponding to the hyperparameter setting with highest mean AUC reported for each classifier. We also include the performance of a classifier with the same aforementioned hyperparameters trained on our annotated data. The annotated data is described in Table 4.

### 2.3. Machine learning based risk detection

Our fentanyl use risk codebook is extensive to capture the multiple facets of risk surrounding the use of this substance, but this extensive nature makes it intractable and expensive for experts to label every post/comment. Therefore, to understand discursive risk on r/fentanyl, we built multiple machine learning classifiers using the content annotated by domain experts. Generally speaking, classification is the process of predicting the class of given data points. We built four classifiers, established in the literature, using the annotated data: logistic regression, Support Vector Machine (Noble, 2006), random forest (Breiman, 2001), and long short-term neural network (LSTM) classifiers (Hochreiter and Schmidhuber, 1997). These classifiers used features that captured the frequency, co-occurrence of words and rarity of words in posts specific to a risk code. We used 80% of our annotated data to train our models (that is, the models learned patterns embedded in the data) and tested on the remaining 20% (that is, based on the patterns learned during training, for an unseen data point, the models guessed which category it was the most likely to belong to). Since we had significant class imbalance, we employed SMOTE, or (Chawla et al., 2002). Further details of our models are expanded upon in the “Classification Models” section of the supplementary document. In summary, our classifiers used the language within our expert-annotated posts and comments to predict whether the risk level assigned by domain experts indicated low risk or elevated risk (Fig. 1).

### 3. Results

The performance of our risk models is summarized in Table 5 and includes the mean precision, recall, F1, accuracy and AUC across each fold corresponding to the hyperparameter setting with highest mean AUC reported for each classifier. We also include the performance of a classifier with the same aforementioned hyperparameters trained on our entire training set and tested on our test set. On our test set each model’s accuracy ranged from 0.74 to 0.76, precision from 0.71 to 0.76, and recall from 0.73 to 0.79. However, the differences between the models were not statistically significant when one considers the standard deviation across each metric in Table 5 during cross validation. In summary, no model outperformed another on risk level classification. Lastly, while our models seem to have performed similarly on posts and comments, such as our LSTM model correctly classifying 8 of the 10 posts in our test set, there are too few posts to draw conclusions about the performance comparing posts and comments.

Additionally, to ensure our models were learning signals directly relevant to the risk of fentanyl and thus establish the construct validity of our models (O’Leary-Kelly and Vokurka, 1998), we created a baseline model using length of the text and the number of drug occurrences as features to compare with our more complex language models (or the
Based on Table 5, all our models outperformed this baseline of 0.62 F1 score. We note that each of our classifiers performed similarly with respect to F1 score on the held-out test set: the F1 scores for each classifier range from 0.72 to 0.75. We can also see in the ROC curves in Fig. 2 that the models perform similarly with respect to false positives and false negatives as the decision boundary threshold is varied. Relatedly, each model has a similar AUC. To elucidate these results further, Fig. 2 presents the ROC curves for each classifier.

For simpler classification models like random forest, logistic regression and support vector machine, one can quantify the importance of features by ranking the coefficient of each feature in the trained model, higher the coefficient implies higher correlation of the feature with the positive class (in our case high-risk class). Table 6 shows the top 15 important features (words or phrases) in the risk classification task. As expected, the word “drugxyz”, which is used to represent community specific drug names like “fent” and “carfent,” features prominently in the top two salient words or phrases for every classifier. We further observe that the first person pronoun “I” appears in the top 15 most important words or phrases for our random forest and logistic regression classifier, and the phrase “I know” is in the top 15 for our support vector machine classifier. Upon inspection, “I know” is likely correlated with elevated risk because the phrase is used to bolster one’s credibility when providing advice, such as “I know because I’m a regular fentanyl user”, to provide social proof (Cialdini, 1987) when giving advice, “I know people who...”, and to hedge (Lakoff, 1975) risky personal narratives, such as “I know it’s stupid but...”. Moreover, words associated with procurement, such as “get” and “buy”, and dosing, such as “mg” and “one,” appear in the top 15 most important words and phrases for our random forest and logistic regression classifiers. Meanwhile, the word “terrible,” which is associated with withdrawal and drug use personal narratives, appears in the 15 most important words and phrases for both our logistic regression and support vector machine classifiers. It is important to note that our neural network based LSTM model cannot be

---

**Table 4**

Annotated data statistics.

<table>
<thead>
<tr>
<th></th>
<th>Low risk</th>
<th></th>
<th></th>
<th></th>
<th>Elevate risk</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># users</td>
<td># avg. words</td>
<td>Intake</td>
<td>No-intake</td>
<td># users</td>
<td># avg. words</td>
<td>Intake</td>
<td>No-intake</td>
</tr>
<tr>
<td>Posts</td>
<td>2</td>
<td>177</td>
<td>0</td>
<td>2</td>
<td>40</td>
<td>255</td>
<td>31</td>
<td>9</td>
</tr>
<tr>
<td>Comments</td>
<td>144</td>
<td>55</td>
<td>103</td>
<td>9</td>
<td>205</td>
<td>135</td>
<td>156</td>
<td>49</td>
</tr>
<tr>
<td>Total</td>
<td>146</td>
<td>28</td>
<td>128</td>
<td>10</td>
<td>245</td>
<td>162</td>
<td>187</td>
<td>58</td>
</tr>
</tbody>
</table>

---

Fig. 1. Confusion matrix for each classifier. (LR — low risk, ER — elevated risk).
4. Discussion

In an effort to alleviate the severe public health threat fentanyl misuse poses (CDC, 2018), the present study utilizes machine learning supported by manual domain expert annotation on data from a public, anonymous forum, r/fentanyl, to identify content with elevated risk factors around fentanyl misuse. This way our findings provide novel data and language analytic methods on the study of specific risky behaviors associated with substance misuse. Notable strengths of this paper include the use of a popular social media platform that protects users' privacy while facilitating authentic conversation around stigmatizing or incriminating topics. This allows us to evaluate firsthand experiences, fentanyl misuse and personal risk factors among a high risk and masked population to adapt prevention and rehabilitation programs effectively. Summarily, our work may help support the development and provision of timely treatment and interventions to those in need, while also expanding outreach methods to populations that are difficult to reach via traditional means.

4.1. Practical implications

This research shows that the anonymity afforded by social media sites like Reddit allows individuals to discuss stigmatized topics such as illegal substances (Birnholtz et al., 2015) and fentanyl misuse. Moreover, some of these individuals may be at elevated risk that could be detected via computational methods; consequently, this work can pave the way to provide preventative support or clinical intervention to especially vulnerable individuals on these forums. Furthermore, the r/fentanyl forum facilitates conversation surrounding harm reduction and information about fentanyl and its analogues, providing both a place for advice seeking and social support, as well as an exchange of information related to the use of these substances. Reddit’s popularity and ability to facilitate discussion on specific stigmatizing topics, coupled with the computational methods developed in this work can, therefore, aid in both the timely and targeted outreach to fentanyl misusers, an especially hard-to-reach population (Miller and Sonderlund, 2010; Wejnert and Heckathorn, 2012). This may, in turn, satisfy the need to identify individuals for harm reduction interventions, while maintaining their privacy and encouraging real conversations among other individuals using fentanyl, which may be therapeutic or harm reducing within themselves (Latkin et al., 2003).

Especially in light of increased treatment barriers due to COVID-19, utilizing accessible methods to learn about, target and engage high-risk members of difficult to reach communities in treatment is critical. Accordingly, given the above noted potential for practical use, we discuss two implications for online communities discussing substance use and misuse.

First, prior research suggests that Reddit moderators play an active role in managing the content on their subreddit, defining community-specific rules, establishing norms, and providing support to people who post acutely concerning content (De Choudhury and Sushovan, 2014; De Choudhury et al., 2016; Chandrasekharan et al., 2019). Moreover, auto-moderation tools play an important role in subreddit moderation, empowering moderators with technology-mediated approaches for triaging concerning content, especially in contexts where fully manual triage might be demanding on moderators’ time and effort (Jhaver et al., 2019). In fact, research by Matias et al. that conducted an online experiment on auto-moderation strategies has found the approach to be helpful to content moderation, as well as to enforce and uphold community norms against harassment (Matias, 2019). In light of this research, our work could inform the design of tools to support the work of substance use related online community moderators. For instance, our results could inform the design of tools to help moderators target users posting risky content for interventional outreach, as discussed in recent studies on marginalized populations appropriating social media for health needs (Andalibi et al., 2016; Saha et al., 2020; Wadden et al., 2021). Facebook similarly uses artificial intelligence (AI) to provide resources to those identified as being at risk for suicide based on a partnership with the National Suicide Prevention Lifeline (Constine, 2017), and in March 2020 Reddit announced a partnership with Crisis Text Line to allow users to flag other users who may be in crisis (Perez, 2020). We envision that by pairing our computational approach and using content contributed by non-profit organizations for targeted outreach, moderators will be better equipped to deal with risky messages, in turn, not only helping improve the overall quality of discussions in these forums, but also generate for and share information with public health entities about strategies to invest in prevention and intervention campaigns.

Notwithstanding these opportunities and implications for content moderation, we strongly discourage using our methods to remove content or ban users from posting on these forums. As shown by Chancellor et al. in the context of online pro-eating disorder communities, content removal can be both ineffective and harmful for addressing deviant behavior on social media (Chancellor et al., 2016). When individuals experience vulnerability, they tend to reach out to others to “buffer”...
themselves against negative emotions and actions, and online communities provide one such powerful mechanism (Coyne and Downey, 1991). Therefore, any intervention, based on this work, to empower the community moderators would need to ensure that communities like the one studied in this paper, continue to provide an outlet to seek out these kinds of “safety valves” to individuals to regulate their emotions when they need (Acton, 1973).

Second, we note that past studies among Reddit users misusing opioids (Cavazos-Rehg et al., 2019; Cavazos-Rehg et al., 2021) identified numerous barriers to treatment (e.g., stigma/shame, attitudes towards treatment, treatment readiness) and such barriers may also be reflected in limited openness to direct, proactive outreach strategies among users within these online communities. As a potential approach towards addressing this challenge, based on prior research on peer support in online health communities (Yang et al., 2019; Yang et al., 2019a), our work could be used to empower community moderators, such that they can make appropriate support provisions involving veteran members or other supportive members in the community, who are willing to do so and have been screened to be equipped to help. In addition, our work could be used to connect with and directly query members of communities for specific input to inform feasible, acceptable, and actionable methods of outreach to reduce harm and provide support to better tailor the use of such risk information when detected. These above approaches will certainly have to be tempered with appropriate privacy protections and ethical considerations, so that individuals continue to feel safe in the attempts to discuss substance misuse challenges on online forums, and so that risk detection does not increase harm.

4.2. Methodological implications

Next, there are some methodological implications worth discussing related to implementation. As mentioned earlier, no model performed

<table>
<thead>
<tr>
<th>Category</th>
<th>RF</th>
<th>LR</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic Regression</td>
<td>0.038</td>
<td>1.064</td>
<td>1.046</td>
</tr>
<tr>
<td>Linear SVM</td>
<td>0.025</td>
<td>0.797</td>
<td>0.796</td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.017</td>
<td>0.699</td>
<td>0.699</td>
</tr>
<tr>
<td>LSTM</td>
<td>0.016</td>
<td>0.645</td>
<td>0.645</td>
</tr>
</tbody>
</table>

Table 6
Comparison of top features across three top performing classifiers. Weights denote the feature importance.

Fig. 2. ROC (receiver operating characteristic) curves for each classifier.
statistically significantly better than another across accuracy, precision, recall, and f1, but Fig. 2 shows the sensitivity and specificity tradeoffs associated with each model’s output decision boundary thresholds for binary classification. The preferred threshold would depend on the application of this classifier in a real-world scenario. For example, if a risk classifier with low specificity is used to support moderators of a drug related online community, then the implications of a community member being falsely detected to post risky content could alienate users and suppress the potential use of these online communities as a "safety valve," a concern echoed by Chancellor et al. (2016) and Jhaver et al. (2019). On the other hand, clinical use of the insights of the risk detection model for screening purposes may prefer greater false positives over greater false negatives, because it would minimize the likelihood that individuals showing exacerbated levels of risky fentanyl use are missed and therefore precluded from getting an intervention. Future research must carefully consider these tradeoffs when deciding on decision boundary thresholds.

Although each model performed similarly on classification, there are noticeable differences in how easy the models’ features and decisions are to interpret and audit. For instance, our LSTM neural network model used BERT embeddings (Devlin et al., 2018), representing each post or comment as a $512 \times 768$ matrix, features that are difficult to interpret directly. On the other hand, the n-gram feature vectors, or vectors made by counting words and phrases in the text, used by our logistic regression model and SVM model, are easier to interpret directly. Additionally, it is easier to understand the output of a logistic regression classification model than an LSTM because the former classifies by applying a simple, linear function to input vectors. Meanwhile, LSTM model outputs are complex functions of their input vectors. This means it would be easier for a domain expert to audit the output of our logistic regression model with n-gram features than our BERT LSTM model. As we saw no significant classification improvements between our logistic regression and LSTM models, those using this work should prefer the simpler logistic regression model to the latter to empower domain experts to more easily audit model outputs.

Additionally, the list of community specific drug names we found to improve our models in Table 8 can inform future research on online communities where opioids, fentanyl or fentanyl analogues are discussed. For example, Sarker et al. (2019) found a statistically significant correlation between Pennsylvania county-level overdose death rates and the misuse-indicating social media posts labeled using a machine learning classifier built on a set of "prescription and illicit opioid names, including street names and misspellings" to collect opioid-mentioning Twitter posts. Balsamo et al. (2019) used similar methods to construct a vocabulary of over 700,000 terms associated with opiate related subreddits, but fentanyl analogues appear infrequently because the list was constructed from multiple opiate related subreddits and terms occurring in less than 100 posts or comments were removed. Furthermore, Balsamo et al.’s (2019) vocabulary is not annotated for drug names. Our approach that focused on automatic identification of fentanyl analogues extends this research, opening opportunities for future work that examines harm reduction strategies associated with various genres of opiates.

Moreover, while our aforementioned vocabulary is applicable to the narrow domain of fentanyl analogues, our method of using word embeddings to find online community specific drug names, discussed in the “Data Filtering for Annotation” section of our supplement, can be used to help clinicians understand other colloquial drug names. Notably, Lee and Antin (2012) found a misalignment between the drug names used by substance use researchers and those used by adult drug users. As such, our method may help clinicians better design surveys using colloquial drug names.
An analysis of the misclassified posts in Table 9 also points to some interesting insights. We observed that drug color attributes could not be detected by our classifier. This can be attributed to the rarity of color attribute in our annotated dataset and also gives an insight into how people on the r/fentanyl subreddit talk about drug attributes. We also observe that Dilaudid (brand name for opioid analgesic) is missing in our corpus of drug names to debias, which points to the fact that external sources of drug names or brand names for drugs could be used to supplement this corpus to enhance classification performance of risk detection. We also include examples which were low risk but were classified as elevated risk. These two instances point to our intentionally restrictive codebook which emphasizes on factors like regular user or high tolerance and does not annotate instances with only a mention of usage as risk.

### 4.3. Limitations, conclusions, and future directions

We acknowledge some limitations towards generalizability posed by the focus on a single online community, r/fentanyl. While there are other subreddits on substance misuse that could have been considered in this research, this particular forum allowed us to scope a dataset comprising postings on an opioid frequently misused. Our work also does not consider lurkers on the Reddit platform — individuals who browse and consume content but do not post; in fact, it is noted that for most online platforms, a small minority of users generate a majority of the content (Van Mierlo, 2014). In the light of these issues, we caution against drawing generalizable conclusions about population-level trends on fentanyl misuse behaviors and risk factors beyond the one studied.

A second limitation of our study is that our codebook and risk classifiers label the risk of individual posts or comments based solely on their text versus exploring self-reported user level risk. In addition, our codebook and classifiers can struggle to classify the risk of comments which are ambiguous out of the context of their parent post and surrounding comments. Also, our list of drug names for debiasing does not include every possible drug name, so the comment “Dilaudid only seems to give me a rush if it’s my first shot of the day. Weird. Fu-f is water soluble though?” was likely misclassified because the brand name opiate “Dilaudid” was not in our drug name corpus. Furthermore, our codebook was developed using both inductive (e.g., reviewing r/fentanyl approaches) and deductive approaches (e.g., referencing past literature on opioid/fentanyl risks) to be used with posts and comments on r/fentanyl, so it may not transfer to more general online communities related to opioids. Accordingly, future work could explore user-level opioid use risk based on a user’s entire posting and commenting history. Further more, future studies can explore trends in the occurrences of community specific drug names over time to understand the rise and fall in popularity of specific fentanyl analogues. On a related note, although we did not apply our risk classifier to automatically label the unlabeled posts

### Table 8

<table>
<thead>
<tr>
<th>Seed word(s)</th>
<th>Drug-related words from embedding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fent &amp; fentanyl</td>
<td>herein (0.95), hcl (0.95), analog (0.9), analogue (0.9), opioid (0.89), fentanyl (0.86), analgesic (0.85), acetyl (0.85), carfentanil (0.85), tetrahydrofuranfentanyl (0.85), maf (0.84), heroin (0.84), morphine (0.84), nar-2096 (0.83), 4-hydroxyfentanyl (0.83), carfentanyl (0.83), butyryl (0.83), hcl (0.82), opiate (0.82), furanyl (0.82), acetyl (0.81), butyryl (0.81), acetyl (0.81), acetyl (0.81), citrate (0.81), hcl (0.81), ope (0.8), carf (0.8), r-30490 (0.8), fenta (0.8), carfentanil (0.8), spice (0.8), fentan (0.8), fenta (0.8), 4-fluor (0.79), junk (0.79), transq (0.79), butyril (0.79), drug (0.78), dart (0.78), act (0.78), r30 (0.78)</td>
</tr>
<tr>
<td>Butyr</td>
<td>furanyl (0.99), acetyl (0.99), citrate (0.99), cyclopropyl (0.99), iso (0.99), fuf (0.98), acetyl (0.98), butyryl (0.98), morphine (0.98), acetyl (0.98), 4-furanylfentanyl (0.98), u47700 (0.98), isobutyrylfentanyl (0.98), butyrfentanyl (0.98), 3-methyl (0.98), butyryl (0.98), 4-app (0.98), benzyl (0.97), 4-mec (0.97), thf (0.97), fenta (0.97), acrylfentanyl (0.97), para (0.97), 3-mf (0.97), acetylfentanyl (0.97), snow (0.97), bf (0.97), dixm (0.97), 3-mf (0.97), 2-mef (0.97), fentanyl (0.97), isotominizone (0.97), analgesic (0.97), cocaine (0.97), acetanilide (0.97), methoxyacetylfentanyl (0.97), flooro (0.97), sedative (0.97), noid (0.97), flooro (0.97), thiofen- tanyl (0.97), 3-fluor (0.97), 3-mef (0.97), 3-mec (0.97), methylfentanyl (0.96), diamorphine (0.96), benzylfentanyl (0.96), logue (0.96), salvia (0.96), benzyl (0.96), alprazolam (0.96)</td>
</tr>
</tbody>
</table>

An analysis of the misclassified posts in Table 9 also points to some interesting insights. We observed that drug color attributes could not be detected by our classifier. This can be attributed to the rarity of color attribute in our annotated dataset and also gives an insight into how people on the r/fentanyl subreddit talk about drug attributes. We also observe that Dilaudid (brand name for opioid analgesic) is missing in our corpus of drug names to debias, which points to the fact that external sources of drug names or brand names for drugs could be used to supplement this corpus to enhance classification performance of risk detection. We also include examples which were low risk but were classified as elevated risk. These two instances point to our intentionally restrictive codebook which emphasizes on factors like regular user or high tolerance and does not annotate instances with only a mention of usage as risk.

### Table 9

<table>
<thead>
<tr>
<th>Type</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevated risk misclassified as low risk</td>
<td>Orange is not legitimate , you ‘ve been scammed. The color is interesting, looks oxidized. I would love to see this analyzed, as I’ve only seen white or waxy yellow CF. How can I get the nausea and vomiting under control?</td>
</tr>
<tr>
<td>Low risk misclassified as elevated risk</td>
<td>true pure MAF is stronger than plain ole fent (in my experience it is at least 2x potency when pure, as my dose was effectively halved going from fent to maf) however since maf is no longer being synthesized what remains is degrading and probably cut to hell limited stocks . I know that 3 to 7 hours is good legs trust me that fluoroisobutylfentanyl I had to dose every hour !</td>
</tr>
</tbody>
</table>
and comments in the r/fentanyl subreddit, future research could do so to examine the prevalence of risk in different discussions pertaining to fentanyl and its analogues, as well as study how they evolve over time. It would also be worthwhile to harness similar accessible and secure technology over a larger sample to gather additional rich qualitative data and expand upon both the population and its specific members’ unique needs. This will ensure tailored, efficient measures are targeted and delivered to those individuals most in need.

In using an interdisciplinary approach including machine learning techniques and clinical human coding posts/comments regarding the misuse of fentanyl and its analogues, our team was able to automatically detect risk and identify users who may benefit from substance use support and intervention. This work improves upon our understanding of substance misuse risk factors and furthers our ability to identify such risk concepts among underrepresented populations to inform outreach and intervention strategies tailored to this at-risk group. The findings in this study will not only help to create novel, efficient methods to successfully identify those at high risk for fentanyl misuse, but may also inform future studies aiming to develop and adapt similar models to facilitate timely detection of other substance use and mental health risk factors.

Declaration of competing interest

The authors have no conflicts of interest to report.

Acknowledgements

Funding for this work was provided by the National Institutes of Health (NIH) [Grant No: K02 DA043657 (Dr. Cavazos-Rehg) and Grant No: R01MH117172 (Dr. De Choudhury)], and through a postdoctoral fellowship to Dr. Aledavood from the James S. McDonnell Foundation. We would also like to acknowledge Vivian Aghoborvbare and Nnenna Anako for their work to manually code posts and comments for this study.

References
