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The Efficacy of PRISTINE: Revealing Concealed Opioid Crisis Trends via Reddit Examination

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Abstract

This work is an extension of our previous efforts to combat the drug abuse epidemic which has been on the rise in the past few years []. We expand our developed framework PRISTINE ((o**p**ioid c**r**is**is** de**t**ect**i**on o**n** r**e**ddit)) to investigate the effectiveness of the framework on detecting opioids crisis trends on an expanded dataset from the two subreddits r/dugs and r/opiates. In this endeavor, we demonstrate the effectiveness of utilizing the DQE algorithm in identifying drug-related and evolving drug terms. we conduct comprehensive case studies for the seven drug categories and showcase the most associated keywords for each drug class and their slang/street names. In addition, we provide a case study on one of the most significant opioid crisis contributors to drug overdose deaths in the United States. Our case studies revealed hard-to-find drug-related terms which we hope to contribute to mitigating this crisis. We additionally include a new analysis to investigate the efficacy of applying PRISTINE in categorizing subreddits into fine-grained drug classes. The new analysis includes a case study that classifies anonymized and lengthy subreddit comments into their correct drug class. The analysis shows the strong performance of PRISTINE and demonstrates that

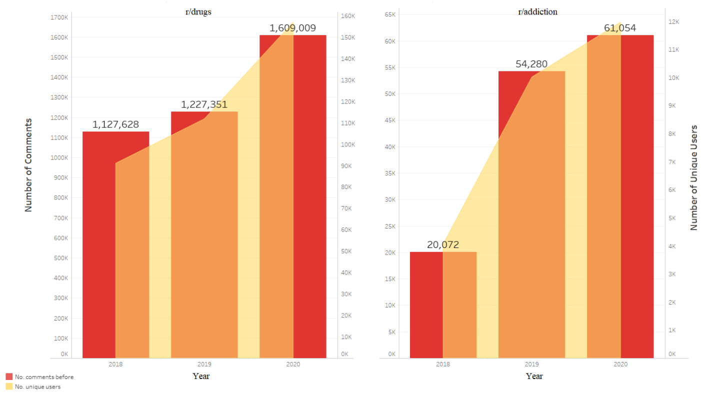

Fig. 1 The chart on the left addresses initial observations of the number of comments and unique users in the 'r/Drugs' subreddit, and the right chart addresses the' r/addiction' subreddit between the period 2018-2020. The left Y-axis for both charts denotes No. of comments, and the right Y-axis denotes the No. of unique users. The dark red bars are the No. of comments, and the grey area is for the No. of unique users.

the framework can be applied to a wide range of subreddit comments. We finally include the performed extensive experiments to show the effectiveness of the overall performance of the proposed framework.

Keywords: Effectiveness, Examination, PRISTINE, Trend

1 Introduction

Over the past decade, more than half a million people in the United States have lost their lives due to drug overdose, a devastating issue affecting individuals across the nation. Excessive consumption of substances, including prescription drugs, over-the-counter medications, and illicit drugs, can result in drug overdose, causing severe harm to bodily functions such as respiratory and cardiovascular systems. The drug overdose epidemic not only devastates families and communities but also overwhelms healthcare providers and mental health services, highlighting the urgent need for effective prevention and treatment. Unfortunately, the COVID-19 pandemic has worsened this already dire situation. Nearly 92,000 (an increase of 29%) people died from a drug-involved overdose in 2020, including illicit drugs and prescription opioids. Deaths involving synthetic opioids other than methadone (primarily fentanyl)continued to rise with 56,516 overdose deaths reported in the same year[1]. With no end in sight to the drug overdose epidemic, it is crucial that collaborative work among healthcare authorities is introduced to analyze, detect, and focus on the existing and developing drug issues.

In general, individuals who initiate conversations about drugs may seek to obtain drugs, sell them, gather information about them, or ask for help to recover from addiction. In recent years, social media platforms like Twitter, Facebook, Instagram, and Reddit have emerged as useful tools for understanding drug abuse and drug-related conversations. Among these platforms, Reddit stands out as a discussion-oriented platform organized by subject, where drug-related subreddits openly discuss topics like addiction, recovery, harm reduction, therapeutic use, cultivation, or drug-titled ones such as 'r/opiates.' The number of comments and unique Reddit users participating in drug-related subreddits has significantly increased, suggesting an urgent need for attention (see figure 1).

Recent research emphasized utilizing social media data or user-based surveys to understand trends of drug abuse/use and drug-health factors through different methods. Wadekar [2] and Tabar et al. [3] underlined only a specific group of drug users/abusers. Most of the other works concentrated on analyzing drug use/abuse trends [4–11]. Others conducted research on monitoring social media such as Youtube[12], Twitter[13–15], and Instagram[16]. Although those efforts have positively contributed toward critical aspects of combating real-time drug use/abuse issues, they exhibited some crucial challenges.

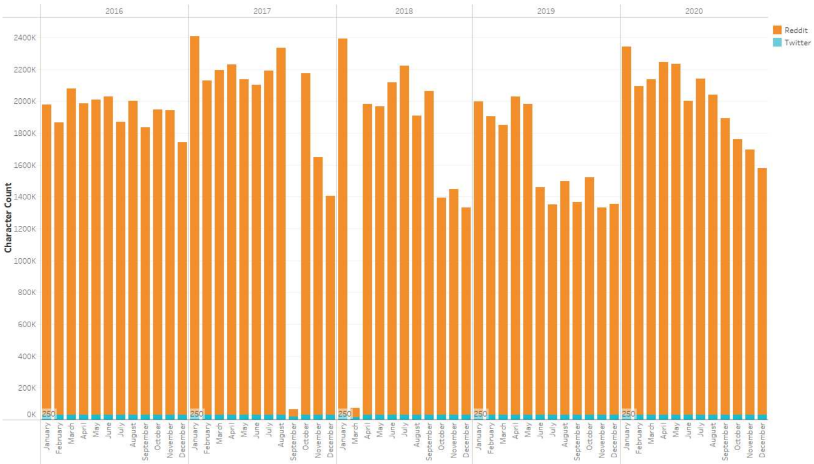

Fig. 2 Subreddits character count distribution. The X-axis shows the months over 5 years. The Y-axis is the character count of each subreddit in r/drugs. The light blue color represents tweets max character count(250)

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Our survey revealed that a majority of researchers focused their efforts on analyzing Twitter data. In comparison to Twitter, Figure 2 illustrates the character count distribution for each month from 2016 to 2020, originating from the r/drugs subreddit, depicted in orange. We highlighted all the subreddits that share the same number of the maximum character limit for a tweet (280 characters). It is evident from this analysis that Reddit posts consistently utilize more characters than their Twitter counterparts. Furthermore, a tweet with 250 characters can encompass a range of 45 to 63 words and accommodate up to 12 sentences. Consequently, we examined the word and sentence counts from the r/drugs subreddit to establish a comprehensive comparison between tweets and subreddit posts. Figure 3 displays the distribution of word and sentence counts across all analyzed subreddits. The reference line at 63 highlights the maximum number of words possible within a tweet. This comparison clearly demonstrates the challenges we faced when addressing the longer text content found in Reddit posts compared to tweets.

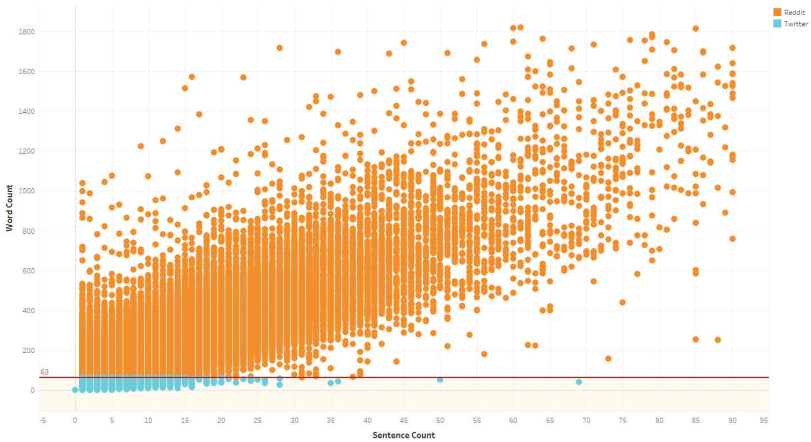


Fig. 3 Word and sentence count distribution of 5 years data from r/drugs subreddit posts. The X-axis displays the sentence count. The Y-axis is the word count. The red reference line shows the at most cases of word counts of tweets (63 words) colored in light blue.

To address those challenges, we developed PRISTINE[17] (o**p**ioid c**r**is**is** de**t**ect**i**on o**n** r**e**ddit), a real-time drug abuse detection model on Reddit data. In particular, the model concentrates on not only distinguishing drug-related comments from regular informative comments but also discriminating to which specific drug class (Narcotics, Stimulants, Depressants, etc.) a comment belongs.

The main contributions of our work are summarized as follows:

- **We present a novel framework to dynamically detect & extract evolving drug names from Reddit data by reinforcing the DQE algorithm.** Our work improves the algorithm, which was specifically designed to expand keywords in short texts like Twitter, to expand keywords in longer texts. Such an enhancement can help in extracting Reddit comments in real-time based on a manually curated list of seed queries which include names and keywords used for drugs based on DEA's & SAMHSA's list.
- **We demonstrate the effectiveness of DQE in identifying relevant and emerging drug names.** We conduct comprehensive case studies for seven drug categories (general cases) and one case study on Fentanyl (specific case). These case studies reveal challenging drug trends for all the categories,

not only detecting slang drug names but also identifying associated terms. We selected Fentanyl, one of the leading causes of the opioid crisis, as a specific drug case to aid in mitigating this epidemic.

- **We investigate the application of PRISTINE in categorizing subreddits into fine-grained drug classes.** To showcase the efficacy of PRISTINE in categorizing Reddit posts, we provide real-world examples of subreddits belonging to each drug class while preserving anonymity. Our case studies encompass a variety of random Reddit posts submitted to PRISTINE for classification purposes. The case studies demonstrate the strong performance of PRISTINE when applied to a diverse range of subreddit comments.
- **We conduct extensive experiments to demonstrate the effectiveness of the proposed framework.** Our framework outperforms 6 baselines on drug abuse classifications. The in-depth experiments demonstrate the superiority of our work on a wide variety of embeddings. Our framework outperforms 6 baselines on drug abuse classifications. We also experiment on wide variety of embeddings to demonstrate the superiority of our work.
- **We include a survey in the field of drug abuse detection.** We expanded the related work section and encompassed the most recent works of drug abuse detection.

2 Related Work

The key components of this work are based on three major concepts: mining social media to detect drug abuse, applying GCN to detect relevant drug abuse comments, and utilizing DQE for event detection. We provide further detail in the respective sections below.

2.1 Drug Abuse Detection

In recent years, a growing body of research has focused on addressing the issue of drug addiction and substance abuse in communities. These studies aim to identify patterns and trends related to substance abuse and develop effective strategies to reduce its prevalence. These studies have utilized various approaches, including statistical and machine learning methods, to analyze data from multiple sources, such as social media, pharmaceutical tabular data, and surveys. Therefore, we divide our discussion of drug-related studies into two categories: those that employ statistical methods and those that use machine learning techniques.

The first category of techniques used to address the drug abuse epidemic involves statistical methods, which analyze social media and statistical data. By examining data gathered from surveys of adolescents, [2] investigated the correlation between various factors that contribute to a comprehensive understanding of adolescents' life and the development of Substance Use Disorder (SUD). Through statistical analysis, the study produced accurate predictions for identifying adolescents who are at risk. From the works that mined social media and analyzed its textual data statistically, [18] suggested a framework consisting of four phases that leveraged Twitter data to investigate drug abuse and tackle issues associated with data quality and topic deduction. The framework involved collecting data, processing it, detecting topics, and evaluating its quality. The LDA topic mining algorithm was employed to identify drug abuse topics. Similarly, [19] conducted topic modeling to identify the main areas of interest, but they used Reddit posts instead. They also computed the statistical significance of the posts and compared the scores to gauge the degree of social support obtained from the comments. Lavertu et al.[8] employed statistical analysis to monitor and dete ct drug-related comments posted by users for more than a decade and evaluated the users' drug-related engagement throughout this duration. Finally, [20] utilized thematic analysis on data gathered from two opioid subreddits to explore how COVID-19 affected the social networks and processes of individuals who use opioids. The results indicate that the pandemic caused alterations in the social networks and daily routines of opioid users. While the statistical analyses yielded meaningful inferences, they did not provide precise forecasts for the drug-related Reddit posts.

The second category of methods used to combat the drug abuse epidemic involves leveraging ML techniques on social media or statistical data. First, Twitter has been the subject of numerous studies. For instance, Buntain et al. [9] studied emerging patterns of illicit drug use by analyzing tweets. They geolocated the tweets and categorized them based on tracking the frequency of drug names over time. Lossio-Ventura et al. [6] aimed to gain insight into drug abuse by evaluating drug-related tweets. To extract drug-related terms, they utilized the LIDF-value measure incorporated in BioTex [21], enabling them to obtain an understanding of the topic. Moreover, tweets were employed by AutoOPU [22] and AutoDOA [13] to automatically identify opioid users as either potential Opioid User/Non-Op User. To reduce the cost of acquiring labeled examples, both works introduced a Heterogeneous Information Network (HIN) and combined meta-path, enabling cost-effective detection. Sarker et al. [23] compared traditional and ensemble ML classifiers for geospatial and temporal analysis of tweets to monitor the opioid crisis. Hu et al. [24] put forward a deep self-taught learning mechanism to identify and track drug abuse risk behaviors in tweets, using a substantial quantity of unlabeled data. Likewise, Sequeira et al. [5] employed a binary classifier to recognize drug-related tweets, which they then utilized to construct a follower network based on topic cascades. Subsequently, Saifuddin et al. [25] employed GNNs and binary classification to identify drug abuse tweets based on 1500 manually annotated tweets. They then constructed a dictionary of drug names and use/abuse to validate tweets by word matching and text similarity measurements, detecting Medication-Assisted Treatment Medication Users (AMMUs).

Conversely, Singh et al. [4] conducted a sentiment analysis of tweets to investigate the substance abuse disorder trend before and during the COVID-19 pandemic. Moreover, Dey [26] recently utilized traditional machine learning classifiers to categorize drug-usage tweets into three main divisions: News tweets, drug-user tweets (sub-divisions: past, current, intent), and Reaction Tweets. Secondly, there have been limited studies conducted on Reddit. Chancellor et al. [27] employed a transfer learning technique to detect Discussions in Reddit posts regarding drug recovery and alternative treatments. Meanwhile, Jha et al. [28] utilized a combination of bidirectional Long-Short-Term Memory networks (Bi-LSTMs) and conditional random fields (CRF) to model addiction stages based on the sequence of Reddit posts, including Use, Withdrawal, Recovery, and Relapse. Finally, two recent works applied ML methods to statistical data. DOD-Explainer was proposed by [29] to predict overdose deaths in the U.S. based on a combination of socioeconomic and crime data and provided explanations for the leading causes of the crisis. Comparably, Islam et al. [30] implemented classical ML classifiers on socioeconomic questionnaire data, but they predicted an individual's vulnerability by identifying key risk factors behind substance abuse. Those endeavors have substantially propelled the field in terms of comprehending, mitigating, and supervising the drug abuse epidemic. However, it is imperative to develop automatic multi-classification tools that are drug-class-specific and deal with the ambiguity posed by street/slang names of drugs. PRISTINE fills this gap, and this paper demonstrates the efficiency of it.

2.2 Graph Convolutional Network for Event Detection

The application of GCN for detecting drug use/abuse in Reddit comments is a substantial phase of our research. GCN has been widely explored for event detection and text classification in social media. Originally, Kipf et al. [31] proposed GCN for node classification, which was later adapted by Yao et al. [32] for text classification tasks. In that work, corpus graphs were constructed with documents and words as nodes, and GCN was employed to learn the word and document embeddings. In a relevant task, Clinical Event Detection (CED), Liu et al. [33] incorporated external knowledge using GCN to enhance the model's performance in identifying event occurrence types. GCN has been applied in additional tasks for event detection, such as predicting the impact of traffic incidents. For instance, Fu et al. [34] proposed a hierarchical learning approach to model local correlations and traffic patterns between sensors. Similarly, Guo et al. [35] utilized spectral clustering to process the graph structure and predict traffic for both micro and macro graphs by learning the spatial relationships between road segments. Despite the effectiveness of GCN as a fundamental technique for event detection, its application in detecting drug abuse in the Reddit comments environment has not yet been explored.

2.3 Dynamic Query Expansion for Event Detection

Dynamic Query Expansion (DQE) is a popular data mining technique frequently used in event detection or forecasting on Twitter[36]. The method harnesses the diverse relationships within the Twitter information network to expand a seed query and improve coverage and accuracy [37]. In a real-time application, DQE was utilized to detect emerging threats related to airport security by tracking and analyzing the related tweets[38]. DQE has also been applied to enhance a multi-task framework for spatial event forecasting in social media[39]. By extracting civil unrest-related tweets, DQE effectively detected civil unrest events[37]. By utilizing multiple query expansion techniques, Khandpur et al. [40] were able to detect cyber-attack events from social media streams. Zulfiqar et al. [41] monitored emerging information from tweets on Metro incidents and threats using DQE. Zhao et al. also employed DQE to track flu outbreaks in tweets[42]. DQE is a suitable technique for Twitter's platform as the method is tailored for handling large volumes of short text. However, our work aims to enhance the algorithm by enabling it to handle long and extensive volumes of Reddit comments. Although DQE may not be a suitable approach for text classification, its primary objective of extracting pertinent key phrases from a given query is achieved with great effectiveness.

3 Methodology

In this section, we demonstrate our model, which categorizes drug abuse based on Reddit comments and establishes relationships between drug classes using a constructed graph, along with an overview of the problems and tasks. To design our model, we first enhance the dynamic query expansion algorithm to extract specific drug-related Reddit comments from the Reddit area. Afterwards, a textual graph convolutional network is constructed. Each component of our model interacts with the others to enhance the capability of identifying drug abuse Reddit comments and create a function that identifies such comments based on their specific drug class.

3.1 Problem Statement

To detect specific-class drug abuse-related comments from the heterogeneous unlabeled Reddit comments, we mathematically define the problem in two parts. The first part defines how the Dynamic Query Expansion (DQE) algorithm extracts a large amount of Reddit comments and uses them for labeling. Then, the second part defines how the labeled comments are used in drug abuse detection with GCN. Those parts work coherently to present an application to detect fine-grained classified drug abuse in Reddit comments.

The input of our approach is the unlabeled heterogeneous collection of all Reddit comments (e.g. in the year 2020) C=$\{C_1, C_2, \ldots, C_k\}$, where k is the total number of comments in the input data of that year. Let $\mathcal{C}$ denote the Reddit space corresponding to a subcollection C_i, Let $\mathcal{C}_\clubsuit$ denote the specific drug-class subspace (e.g 'Hallucinogens' drug-related comments), and let $\mathcal{C}_\diamond = \mathcal{C} - \mathcal{C}_\clubsuit$ denote the rest of the Reddit comments in the considered Reddit space

Definition 1. (Seed Query) A ***seed query*** S_0 is defined as a preliminary set of vocabulary manually selected and semantically coherent words that represent the notion of a specific domain, in our case a drug-class. For example, a potential seed query that focuses on one notion of the drug-class '*Hallucinogens*' can be declared as {'LSD', 'Mushrooms', 'PCP', 'Acid', 'Mescaline'}. The set of manually selected specific-class drug vocabulary reflect the relevance to the target notion '*Hallucinogens*'.

Definition 2. (Expanded Query) is the extended preliminary set of manually selected vocabulary and semantically coherent words of the targeted drug-class comments. The ***expanded query*** is denoted as S_1, and it is automatically generated from S_0 by the Dynamic Query Expansion algorithm. For instance, given a seed query of the drug-class '*Hallucinogens*': {'LSD', 'Mushrooms', 'PCP', 'Acid', 'Mescaline'}, the extended subquery can be set of keywords that include: {'blotter acid' ,'dots', 'microdots', 'sugar cubes', 'mellow yellow', 'sunshine tabs', 'window pane'}. The expanded query extracts Reddit comments that are related to LSD usage and disregards comments that include unrelated-drug abuse common words (see Table 1 for examples).

Task 1: specific drug-class generation. Given a Reddit subcollection $\mathcal{C}$, ***specific drug-class generation*** is the task of distinguishing the related Reddit comments of the same drug-class $\mathcal{C}_\clubsuit$. Thus, the queries can expand based on $\mathcal{C}_\clubsuit$ because it covers relevant information from the same drug class.

Task 2: Expanded and Dynamic Query generation. Given the specific drug-class $\mathcal{C}_\clubsuit$, the task ***expanded and dynamic query generation*** is to generate the set of expanded queries $S = \{s_1, \ldots, s_n\}$ which can extract the relevant comments delivered by $\mathcal{C}_\clubsuit$. Thus, we can use S to extract the specific drug class comments from any collection sets because we now can use a small set of seed queries S_0 and the Reddit collection $\mathcal{C}$. At this stage, we can iteratively expand $\mathcal{C}^t_\clubsuit$ and S^t until all the specific drug-class related comments are included, where t is the number of iterations until convergence.

Definition 3. Detecting drug abuse specific-class comments with GCN. For the given set of Reddit comments C=$\{c_1, c_2, \ldots, c_K\}$ $] \in \mathbb{R}^{K \times F}$, where K is the number of comments in our labeled drug-class Reddit comments from dynamic query expansion and F is the number of features containing the Reddit comments' semantic meanings. The graph represents each comment c_i as a node in the graph, and for the Reddit comments C, then a fully-connected graph representation $G\dagger = (V, E\dagger)$ is built, where V is the correlated node set for the Reddit comments set C and $\mathsf{V} = K$, and where $E\dagger$ is the edge set for the full-connected graph $G\dagger$ ($\mathsf{E}\dagger = \binom{K}{2}$). When the distinguishing conditions ϵ holds, the drug abuse detection textual graph $G = (V, E)$ is built, and the graph G represents the semantic distance between the comments where $E \subseteq E\dagger$.

On the other hand, we create a vector $D = (d_1, d_2, \ldots, d_L)$, where L is the number of drug-class labels. Having all those concepts established, ***Detecting drug abuse specific-class comments with GCN*** is mathematically defined as the learning function F which maps C to D:

$$F(C) \longrightarrow D$$

In detail, given the input data C, the distinguishing conditions ϵ , and the corresponding drug abuse class labels D, learn an optimal solution to accurately determine the type of drug abuse specific-class activities and the relationships among those drug classes when given an unseen drug abuse online comment.

3.2 Dynamic Query Expansion for Reddit

It is a laborious task to mine the tremendous amount of Reddit text, especially when retrieving all drug abuse-related comments using word-matching techniques. In addition, drug-related keywords especially illicit drugs, are not always clearly mentioned, and they are intended to mislead detection by using common words (e.g. the drug 'Psilocybin:Hallucinogens' known as 'Mushroom' can be mentioned in many common misleading names: {'Alice', 'Boomers', 'Caps', 'Magic Mushrooms', 'Mushies', 'Pizza Toppings', 'Shrooms', 'Tweezes'). Therefore, it is a challenging task to not only extract all drug abuse-related Reddit comments but also identify to which drug class those comments correspond.

In a novel way, our work utilizes the dynamic query expansion to retrieve all drug abuse Reddit comments corresponding to a specific drug class and distinguishes the comments that only address non-drug-related comments. Further, we enhance the algorithm proposed by Zhao et al [37] which was initially designed to process small texts such as tweets, so it can handle long text format and can effectively work on Reddit social media platform. By having a small set of seed queries having manually selected keywords, DQE improves the text extraction results. The method is capable of expanding the seed query iteratively from the currently selected target Reddit subspace until it automatically converges.

Algorithm 1 Dynamic Query Expansion Algorithm For Reddit Space

Input: Seed Query S_0, Reddit sub-collection C
Output: Expanded Query Set S
Initialize: $\mathcal{C}^0_\clubsuit = match(S_0, C)$, R_0, $w(R_0) = 1$, $t = 0$
  while $w(R_t) \neq w(R_{(t-1)})$ **do**
    $t = t + 1$
    $w(R_t) = idf(R_t) \cdot A \cdot w(C_{(t-1)})$
    $w(C_t) = \Psi \cdot A' \cdot w(R_t)$
    while $\sigma > 0$ **do**
      $swap(min(w(C_t)), MAX(w(C - C_t)))$
      $\sigma = min(w(C_t)) - MAX(w(C - C_t))$
    end while
  end while
  $S = R_t$

In the displayed pseudo code 1 , the input consists of two parts: the first is the initial seed query S_0 based on manually selected basic and representative keywords for each drug-class, S_0 can formulate the main theme around that drug-class (see Tables 4-10 for examples). The second part C is Reddit subcollection so S_0 can expand on it, and is defined in **(Definition 1)**. The output of DQE S automatically identifies the most related keywords or candidates out of the Reddit subcollection C (see Table 1). We implement enhancements on the key aspects of the algorithm, so it can process long text format which was one of the limitations of the algorithm's performance.

After defining the seed query and Reddit subspace data, we initialize R_t which is the feature node for a Reddit comment, and w which is the set of weights for nodes where higher weights denote a higher degree in relation between the features or comments related to the defined drug-class. Then, the weight of R_t is calculated by *Inverse Document Frequency (IDF)*, the weight of $C_{(t-1)}$, and the adjacency matrix A. The basic algorithm ranks the candidate queries and specifies a certain number of the most related keywords to become the candidate keywords. This could cause a major low performance on Reddit subspace and cause the algorithm to be ineffective. We boost the algorithm by concatenating the candidates so they can expand efficiently and accurately. For example, in one of the iterations the algorithm returns 3000 large text comments it becomes very slow to expand from that number of comments in the space of 200000 and so on. Therefore, we concatenate the most related returned candidate keywords so the algorithm can perform effectively at high speed and accuracy in large text format.

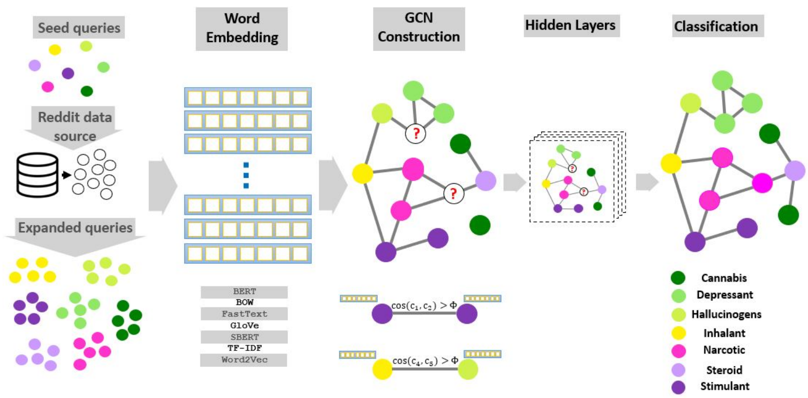


Fig. 4 The illustrative architecture of the proposed PRISTINE method.

Lastly, the algorithm iterates and compares the minimum weight of the related Reddit comments and the maximum weight of the unrelated Reddit comments. This allows it to select only the ones with a higher score and store them in the returned results. After t number of iterations, the algorithm reaches a point of convergence and outputs a representative set of keywords. We use those results to produce high-quality semi-supervised labeled Reddit comments which immensely mitigates the laborious work of manually labeling a large number of Reddit comments , and it distinguishes unrelated drug common words from the targeted drug abuse comments based on a specific class.

Table 1 Examples of Reddit comments extracted by the dynamic Query Extraction according to their drug-class labels from the seed keywords

Reddit Comment	Expanded Keyword	Drug class
One time I had some doses that were on sugar cubes instead of paper.	sugar cube	Hallucinogen
I don't understand how roids make women more manly yet give men tiddies. Doesn't make sense to me.	riods	Steroid
Everyone I know calls it Hippie Crack.	Hippie Crack	Inhalant
Sure she sold him pizza toppings, but she lost her life man	pizza toppings	Hallucinogen

3.3 Textual Graph Convolutional Network for drug abuse specific-class detection

To capture the semantic relationship among the Reddit common posts and their similarities to each other, we construct a textual graph. The graph provides local and neighborly textual perception based on the context similarity among those online comments, as a result reaching a global understanding of the drug categories activities in the Reddit space. Looking back into ***Definition 3***, the textual graph with a partial graph representation is described as $\mathcal{G} = (\mathcal{V}, \mathcal{E}, A)$, where $\mathcal{V}$ is the set of vertices in the graph which correspond to the Reddit comments $C, \mathcal{E}$ denotes the set of edges connecting the vertices, and A denotes the graph's adjacency matrix. The vertices v_i and v_j representing the Reddit comments c_i and c_i respectively in the graph $\mathcal{G}$, the graph's adjacency matrix $A \in R^{N \times N}$ that indicates whether the pair of vertices are adjacent or not can be constructed as the following:

$$A_{i,j} = \begin{cases} (c_i, c_i), & \text{adjacent if } \Phi(c_i, c_i) \text{ condition is satisfied} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

The edge between $(c_i,\ c_i)$ is the cosine similarity calculation between the two vectors; the condition Φ is the textual similarity between the two vectors of the input target c_i and c_i. the condition Φ is selected such as there exists an edge between two nodes c_i and c_i if $(c_i, c_i) \geq \epsilon$. We empirically choose ϵ to cut away as many insignificant or unwanted edges to decrease the complexity of the graph network and maintain the performance of the model. Therefore, the condition only returns true (there exists an edge) if c_i and c_i there is a meaningful semantic similarity between the two nodes.

At this stage the textual graph representation $\mathcal{G} = (\mathcal{V}, \mathcal{E}, A)$ is constructed of the Reddit comments C. Given $\mathcal{G}$, a spectral graph convolution is defined as the multiplication of a signal with a filter in the Fourier space of a graph[31].

A graph Fourier transform is defined as the multiplication of a graph feature vectors for every vertex v) with the eigenvector matrix U of the graph Laplacian L. The Laplacian matrix L (unnormalized Laplacian or combinatorial Laplacian), an essential operator for spectral graph structure, is defined as $L = D - A$, where $D \in \mathbb{R}^{n \times n}$ is diagonal degree matrix with $D_{i,j} = \sum_j A_{ij}$. Having the Laplacian matrix and the degree matrix defined, we calculate the normalized Laplacian matrix $L = I_n - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \in \mathbb{R}^{n \times n}$, where I_n is the identity matrix. The Laplacian matrix L_n is symmetric positive semidefinite, after normalizing it. Its eigen decomposition also known as spectral decomposition, a method to decompose a matrix into a product of matrices involving its eigenvalues and eigenvectors[43], is formulated as

$$L = U \Lambda U^T = U \Lambda U^{-1} \tag{2}$$

U consists of normalized and orthogonal eigenvectors. The Laplacian is diagonalized by the Fourier basis $U = [u_0, ..., u_n \in \mathbb{R}^{n \times n}]$ and the combination of eigenvalues $\Lambda = diag([\lambda_1, ..., \lambda_n])\lambda \in \mathbb{R}^n$. As a result, we can define the spectral convolution in the Fourier domain as the following:

$$d = \sigma(U g\theta(\Lambda) U^T c) \tag{3}$$

where d is the convolution input and c is the output, σ is the activation function, and $g\theta$ is the convolution process filter. All spectral-based GCN act in accordance to this definition of equation 3, the major point of distinction between different version of spectral-based GCN resides in the alternative of the filter $g\theta(\Lambda)$[44]. There are alternatives with expensive computational complexities when there is large-scale graph structures. Therefore, we seek to decrease that computational complexity, we apply an approximation to the filter $g\theta(\Lambda)$. Recalling that the Chebyshev polynomial $T_m(d)$ of n^{th} order, which is recursively defined as $T_n(d) = 2dT_{m-1}(d) - T_{m-1}(d)$, with $T_0(d) = 1$ and $T_1(d) = d$. Thus, this approximation filter is applied to $g\theta(\Lambda)$:

$$g\theta(\Lambda) \approx \sum_{n=0}^{K} \theta_n T_n(\tilde{\Lambda}) \tag{4}$$

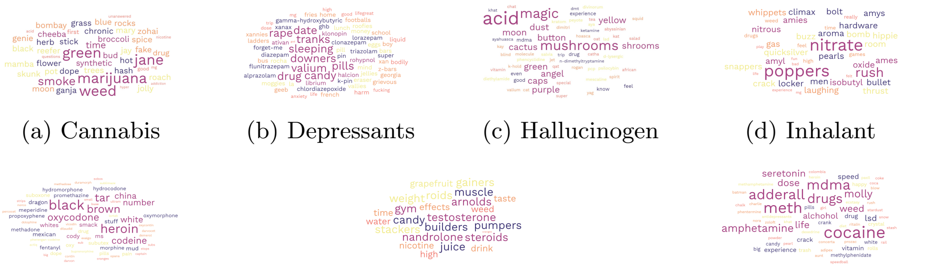
in this formulation of the graph convolution, we further approximate $\lambda_{max} \approx 2$, which was first proposed by Hammond et al.[45]. Under such approximations, it can formulated as:

$$\tilde{\Lambda} = \frac{2}{max_(\lambda)} \Lambda - I_n = \Lambda - In \tag{5}$$

Therefore, the final representation of the graph convolution network introduced by Kipf et al.[31] limited the approximation to the first order of ChebyshevNet by assuming n = 1 and $\lambda_{max} c = 2$. The equation for GCN becomes

$$Z = (D + I_n)^{-\frac{1}{2}} (A + I)(D - I_n)^{-\frac{1}{2}} X\theta \tag{6}$$

Where $\theta in\mathbb{R}^{c\times d}$ is the matrix of filer parameters (c is the input channels, and $zin\mathbb{R}^{n\times d}$ and d is the number of the output channels. At this stage, given the constructed textual graph convolution network $\mathcal{G}\star = (\mathcal{V}\star, \mathcal{E}\star, A)$, where $\mathcal{V}\star$ containing the sentence embeddings of the Reddit comment, and $\mathcal{E}\star$ is the conditioned calculated semantic similarity between the updated nodes in $\mathcal{V}\star$, we utilize the constructed graph for prediction. In summary, $C \in \mathbb{R}^{K\times F}$ is the input to the graph which is the hidden textual features from the sentenced-based comments encoders. The shared information among the related vertices are modeled by the approximation filter g_θ. The vector $D = (d_1,\ d_2,\ \ldots,\ d_L)$, where L is the number of drug-class labels are the output of the graph which predict the specific drug-class label inferred from the features of the neighboring nodes. In this way, the model is employed to classify the unseen drug abuse Reddit comments based on their drug class, so the drug-specific activities can be monitored and analyzed in relation to each other.



(a) Cannabis (b) Depressants (c) Hallucinogen (d) Inhalant

(e) Narcotic (f) Steroid (g) Stimulant

Fig. 5 Query expansion keywords for each drug class

4 Experiments

The primary objective of this study is to identify instances of drug abuse within the extensive space of Reddit comments, classified into specific drug categories such as Cannabis, Depressants, Hallucinogens, Inhalants, Narcotics, Steroids, or Stimulants. This section provides a comprehensive analysis of the experiment's methodology, including baseline models and findings of the experimental results.

4.1 Data collection and extraction:

Subreddits on the Reddit platform are centered around specific topics and are indicated with the prefix "r/". Users participate in these subreddits by posting and commenting on topics of interest. Our survey (refer to section 2) revealed that most drug-related studies focused on Twitter data, while only a few studies utilized drug-related data from Reddit. These studies examined general drug abuse keywords and did not specify which drug class a comment belonged to. To address this gap, we conducted our research following the same standards as the previous studies, but we expanded our focus by extracting fine-grained comments belonging to each of the defined drug classes. Our data was collected from the most popular drug-related subreddits on Reddit between Jan 2018 and Dec 2020. We used PushShift.io [46] to extract all comments and their metadata from the following subreddits: 'r/addiction', 'r/drugs', and 'r/opiates'. The collected data was preprocessed for the experiment by removing special characters, irregular spaces, and stop words.

To facilitate the extraction of drug-specific comments, we merged the data collected from different subreddits. A novel approach we adopted was the use of Dynamic Query Expansion (DQE) to extract comments that were aligned with specific drug classes (as explained in section 3). We developed seed queries for each drug class manually and expanded them dynamically across the consolidated Reddit data. This resulted in a balanced dataset with 8000 comments for each drug class, suitable for our experiment. Examples of the extracted Reddit comments and their corresponding drug classes are presented in Table 1.

4.2 Experiment settings & Baselines

Word embeddings can significantly affect how well contextualized models work[47]. In order to study the efficacy of the word embeddings put on Reddit comments with various classifiers, we experimented with the most effective word embeddings by applying them to all the baselines we experimented with. Word embeddings, to put it briefly, are word vectors that are "dense, distributed, and fixed-length" [48].These vectors can therefore be mathematically processed, for example, by computing the cosine similarity between two vectors. The experimented word embeddings are the following: Bag of Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), Word2Vec, Global Vectors for Word Representation (GloVe), FastText, Bidirectional Encoder Representations from Transformer (BERT), and Sentence-BERT (S-BERT).

- **Bag of Words (BoW)** is a standard feature extraction method from documents that identifies the word occurrences. It is predicated on a set of well-known words and a way to gauge how common those words are. As a result, $C \times K$ represents the matrix of the number of words used in the Reddit comments (C is all the comments and K is the known vocabulary).
- **TF-IDF** extracts features according to statistical measures to identify the importance of words in documents (the whole considered training set). We can get the TF-IDF value by multiplying the TF and IDF values [49].
- **Word2Vec**, first proposed by Mikolov [50] is another widely used technique to build word embeddings based on their linguistic context. We use two techniques to obtain the neural networks-based embedding (Skip Gram and Common BoW).
- **GloVe** distinct from Word2Vec, produces word vectors by combining global and local corpus statistics [51]. In our experiment, we utilized a pre-trained

Table 2 Overall performance of baseline methods in comparison to our method on 8,000 Reddit comments for each drug-class. Embedding(Emb), Percision (P), Recall (R), and micro-F1 (F1)

Emb	LR			NB			KNN			SVM			MLP			XGBoost			PRISTINE		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
BOW	43.2	41.1	42.0	50.9	43.9	47.1	40.7	37.7	39.2	61.0	57.1	59.0	67.2	60.8	63.8	64.2	62.8	63.5	76.3	74.2	75.2
TF-IDF	44.5	42.3	43.4	54.3	46.9	50.3	42.8	38.6	40.6	62.0	58.1	60.0	65.8	59.8	62.7	65.9	63.7	64.8	77.4	75.6	76.5
FastText	45.4	43.1	44.2	47.1	41.1	43.9	45.1	39.4	42.1	65.1	60.9	63.0	68.5	61.5	64.8	70.1	65.8	67.9	79.4	77.7	78.6
W2V	46.3	44.5	45.4	45.1	39.3	42.0	46.0	40.3	43.0	66.2	62.0	64.0	67.1	60.5	63.6	71.9	70.0	70.9	80.6	79.2	79.9
GloVe	47.8	45.4	46.7	46.0	40.1	42.9	46.9	41.2	43.9	67.4	63.7	65.5	69.8	62.3	65.8	73.7	72.4	73.1	82.7	80.6	81.6
BERT	48.7	46.5	47.5	47.9	41.4	44.4	47.9	42.2	44.9	69.2	64.8	67.0	68.4	61.3	64.6	75.9	74.9	75.4	84.0	82.1	83.0
SBERT	51.3	47.5	48.8	49.4	42.6	45.8	48.9	43.1	45.8	70.4	65.9	68.1	71.2	63.0	65.8	77.9	76.7	77.3	**85.2**	**83.6**	**84.4**

Table 3 PRISTINE fine-grained drug class results

	Percision	**Recall**	**F1-Score**
Cannabis	0.870	0.844	0.857
Depressant	0.831	0.813	0.822
Hallucinogen	0.814	0.786	0.800
Inhalant	0.873	0.827	0.850
Narcotic	0.939	0.872	0.904
Steroid	0.803	0.853	0.827
Stimulant	0.837	0.857	0.847
Weighted Avg	0.852	0.836	0.844

GloVe model that was trained on the Common Crawl dataset with 300-dimensional vectors, just like the pre-trained Word2Vec model that we used, which was trained on Google News.

- **FastText** is able to generate vector representations for out-of-vocabulary words, which Word2Vec and GloVe are unable to do due to their inability to generate vector representations for rare words or words not present in their dictionary [52]. We used the pre-trained FastText on Common Crawl with a vector embedding size of 300. Unlike Word2Vec and FastText, previous word embeddings have fixed-length feature embeddings for word representations regardless of context.
- **BERT** word representation model improves on previous methods by producing different embeddings for the same word in different contexts[53]. We used the Huggingface transformers library with all models in our experiment. However, BERT is not designed specifically for sentence embeddings. To address this, we used a variation called **S-BERT**, which employs siamese and triplet network structures to create meaningful sentence embeddings. This reduces the time needed to find similar pairs using cosine similarity from 65 hours to just 5 seconds[54].

We found in our survey (refer to sec 1 and sec 2) that no baseline method has been used to distinguish Reddit comments related to specific drug classes. Therefore, we conducted experiments using multi-label classification models with different word embeddings to evaluate our approach. The models we experimented with include logistic regression (LR), Naïve Bayes (NB), k-nearest neighbors (KNN), support vector machine (SVM), XGBoost (XGB), and multi-layer perceptron (MLP). Each of these models was combined with various word embeddings, as discussed earlier.

4.3 Results & Analysis

Our evaluation of the proposed method and baselines was based on precision, recall, and micro-F1 metrics, as conventionally done. The results, as presented in Table 2, were obtained from the evaluation of six baseline models and our method on 8,000 Reddit comments, using different word embeddings. Our proposed method outperformed the baselines significantly. Among the baselines, LR, NB, and KNN performed poorly when compared to SVM, MLP, and

XGBoost. The impact of word embeddings on the classification performance was evident, except in some cases such as KNN. XGBoost+S-BERT outperformed PRISTINE+Bow and PRISTINE+TF-IDF, which demonstrates how embeddings can improve the classification results. Comparing our work to the top-performing baseline, XGBoost+S-BERT, our method exceeded it by 9.3%, 8.9%, and 9.1% in precision, recall, and F1, respectively.

In Table 3, we presented the performance of PRISTINE on each individual drug class. It was observed that some classes were detected more accurately than others, possibly due to the use of drugs in combination with other drugs, which caused misclassification of the Reddit comment. However, our proposed method, aided by pre-trained embeddings, exhibited significant performance over the baselines. Therefore, we conclude that our method is more suitable for detecting Reddit comments based on their drug class than the available baseline methods.

5 Case Studies

The proposed framework, PRISTINE, consists of several components that are focused on two main goals. The first goal redesigns the DQE algorithm to dynamically uncover and extract evolving drug names from Reddit posts. The second goal implements a textual graph convolutional network to classify each Reddit post into one of the seven drug classes. We set up several case studies to demonstrate the effectiveness of PRISTINE's framework according to each goal. For the first goal, we put the redesigned DQE algorithm under the scope by creating case studies for each class. We corroborate the investigation by conducting a specific study on the drug Fentanyl. For the second goal, we designed case studies for each drug class to exhibit the effectiveness of PRISTINE in classifying Reddit posts. For these case studies, many random Reddit posts are passed to PRISTINE for classification. For all those case studies, actual anonymized Reddit posts are displayed for illustrations.

5.1 Demonstrating the effectiveness of DQE in identifying relevant and progressing drug names

The study showcases the proficiency of (DQE) in accurately detecting pertinent and evolving drug names within various substance categories. We present general case studies for all seven drug classes. Then, we provide a specific case study for a specific drug, "Fentanyl."

5.1.1 General case studies on each drug category (all seven categories)

Cannabis: is the first category of investigation. Cannabis, also known as marijuana, is a psychoactive plant that has been utilized for various purposes throughout human history, including recreational, medicinal, and spiritual use. Cannabis consumption can lead to a variety of short-term effects, such as euphoria, relaxation, and an altered perception of time, as well as potential adverse effects like anxiety, paranoia, and impaired cognitive function[55]. Additionally, long-term use has been associated with an increased risk of mental health disorders, such as depression, anxiety, and psychosis [56]. However, cannabis has also been found to have potential therapeutic applications, including the treatment of chronic pain, epilepsy, multiple sclerosis, and the side effects of chemotherapy[57]. As a result, the legal status and public perception of cannabis have undergone significant changes in recent years, with many countries and states legalizing it for medical and/or recreational use.

To capture the changing cannabis street drug names and identify the relevant terms, we used well-known cannabis terms as seed words for the DQE algorithm. In table4, we used the seed words "cannabis," "marijuana," and "weed". We experimented on two subreddits r/Drugs and r/Opiates, and we present example cases: detecting relevant terms and street names. An example of identifying the relevant cannabis terms, DQE highlighted the terms "phenidate", "painkillers," "oxy," and "MDMA". Phenidate is short for Methylphenidate (MPH) which is commonly prescribed for the treatment of Attention Deficit Hyperactivity Disorder (ADHD) and is often used illicitly by young adults. Illicit users often coadminister MPH with marijuana[58]. While it is not a common practice to mix opiates with marijuana, some users may choose to combine these substances to achieve desired effects. Some users may consume marijuana and opiates concurrently, such as smoking marijuana while also taking a prescription opioid painkiller or using heroin. This could involve smoking, vaping, or consuming marijuana as edibles and taking opiates orally, snorting, or injecting them. It is essential to note that mixing opiates with marijuana can be dangerous due to the potential for adverse reactions and increased risk of overdose. Further, we were able to identify different progressing street cannabis terms such as "Hasheesh," "Ganja," Grass," and "Cheeba" (see table4 for more examples). The expense of using the DQE is the results may generate a lot of noise, and it does not work independently as the sole method for semi-supervised labeling but rather as an asset to PRISTINE.

Table 4 The table shows the used seed query for Cannabis and examples of the result from two datasets

Seed Keywords	Expanded Keywords
'Marijuana', 'Weed', "Cannabis"	'smoke', 'vape', 'inhale', 'weed', 'pot', 'Cheeba', 'Chronic', 'Dope', 'blunt', joint', Flower', 'Ganja', 'Grass', 'Green', 'hasheesh', 'Hash', 'Herb', Jane', 'JollyGreen', 'Mary Jane', 'Pot', 'Roach', 'Reefer', 'Skunk', 'Smoke', 'Trees', 'Black-Mamba', 'Genie', 'Spice', 'spiritual', 'alcohol', '420', 'Bud', 'Broccoli', 'MDMA', 'oxy', 'paranoid', 'painkillers', 'phenidate'

Depressants: is the second category of exploration. Depressants, also known as central nervous system (CNS) depressants, are a class of psychoactive substances that function by slowing down brain activity, leading to feelings of relaxation, sedation, and reduced anxiety [59]. Commonly used depressants include alcohol, benzodiazepines, barbiturates, and non-benzodiazepine sleep aids [60]. Short-term use of these substances can lead to drowsiness, impaired cognitive function, delayed reaction time, and decreased motor coordination [61]. However, long-term use or abuse of depressants can cause physical dependence, addiction, and a range of adverse health effects, such as respiratory depression, memory problems, and increased risk of accidents or injury [62]. Despite their potential risks, depressants play a crucial role in the medical field. They are prescribed for the treatment of various conditions, including anxiety disorders, insomnia, and seizure disorders[63].

In order to detect and track the relevant and changing street names of depressants, we employed commonly known depressant terminologies as seed words for the DQE algorithm. In table5, we used the seed words "Ativan," "Halcion," "Klonopin," "Librium," "Rohypnol," "Xanax," "GHB," "Hydroxybutyric," "Lorazepam," "Triazolam," "Clonazepam" and "Chlordiazepoxide". We conducted experiments on two subreddits, r/Drugs, and r/Opiates, showcasing sample cases that involve detecting pertinent terms and street names. An instance of pinpointing pertinent terms related to depressants is the expanded keyword "heroin". Although combining heroin with depressants is not typical behavior, certain individuals might opt to mix these substances in pursuit of their desired outcomes. The combination of these substances can cause significant respiratory damage, depression, overdose, and death due to their synergistic effects on the central nervous system. Both heroin and depressants slow down the body's functions, and when used together, they can amplify each other's effects. This increases the risk of severe side effects, including unconsciousness, coma, and even death from respiratory failure. It is crucial to avoid using heroin or other opioids in combination with depressants. Additionally, we successfully identified various evolving street names for Depressants, such as "roofies," "vallies," "schoolbus" and "downers' (see table5 for more instances). Nevertheless, we encountered extraneous keywords like "interested" and "abuse," indicating that relying solely on the DQE method may not be sufficient.

Table 5 The table shows the used seed query for Depressants and examples of the result from two datasets

Seed Keywords	Expanded Keywords
'Ativan', 'Halcion', 'Klonopin', 'Librium', 'Rohypnol', 'Xanax', 'GHB', 'Hydroxybutyric', 'Lorazepam', 'Triazolam', 'Clonazepam', 'Chlordiazepoxide'	'relaxed', 'heroin', 'drowsy', 'sleepy', 'hearing', 'anxiety', 'flunitrazepam', 'diazepam', 'alprazolam', 'downers', 'SleepingPills', 'K-Pin', 'Pin', 'valium', 'SuperValium', 'DateRapeDrug', 'Forget-MePill', 'LaRocha', 'MindEraser', 'roofie', 'Eggs', 'Moggies', 'Vallies', 'Bars', 'Ladders', 'SchoolBus', 'Xan', 'Xannies', 'xanny-it', 'Z-Bars', 'Geebies', 'insomnia'

Hallucinogens: is explored as the third category. Hallucinogens, also known as psychedelic substances, are a diverse class of psychoactive compounds that alter perception, cognition, and mood, often producing profound and sometimes mystical experiences[64]. Common hallucinogens include lysergic acid diethylamide (LSD), psilocybin (found in "magic mushrooms"), dimethyltryptamine (DMT), and mescaline (derived from the peyote cactus)[65]. The effects of hallucinogens can vary widely depending on the substance, dosage, individual's mental state, and environmental factors. Typical effects include visual and auditory hallucinations, distorted perception of time and space, synesthesia, and intense emotional experiences[66]. While the potential for addiction and physical harm from hallucinogens is generally lower compared to other psychoactive substances, there are still risks involved, such as "bad trips," which can lead to severe anxiety, paranoia, and delusions[67]. Moreover, individuals with a personal or family history of mental illness may be at an increased risk for the triggering or exacerbation of psychiatric symptoms[68]. In recent years, there has been a resurgence of interest in the therapeutic potential of hallucinogens, particularly for the treatment of mood disorders, anxiety, and addiction[69].

To identify and monitor the evolving street names and associated terms with Hallucinogens, we used well-known terms related to Hallucinogens as seed keywords for the DQE algorithm. We used the following seed keywords as input into DQE algorithm: "LSD," "Ayahuasca," "Mushrooms," "PCP," "Acid," "Mescaline" , "Psilocybin" and "Salvia" (see table6. We carried out experiments on two subreddits, r/Drugs, and r/Opiates, demonstrating example scenarios in which relevant terms and street names were detected. Examples of identifying relevant terms associated with hallucinogens are the expanded keywords "trip" and "experience". A drug "trip" refers to the altered state of consciousness, perception, thoughts, and emotions experienced after consuming a psychoactive substance, particularly hallucinogens such as LSD, DMT, psilocybin, and mescaline. Further, when a hallucinogen such as Salvia can induce a range of subjective "experiences," such as perceptual distortions, visual and auditory hallucinations, time distortion, and a sense of dissociation or disconnection from reality[70]. Using hallucinogens or other psychoactive substances carries potential risks, and it is essential to be aware of these risks. Moreover, we effectively detected numerous evolving street names for depressants, including "Lucy," "Superman," "Khat," Shrooms," "Dimitri" and "Mescal" (refer to Table 6 for additional examples). However, we came across unrelated keywords such as "way" and "place," suggesting that relying exclusively on the DQE approach might not be adequate.

Inhalants: are a diverse group of volatile substances that are intentionally inhaled to achieve psychoactive effects, often referred to as "huffing," "sniffing," or "bagging." These substances include solvents, aerosols, gases, and nitrites, commonly found in everyday household products such as glue, paint thinner, lighter fluid, and whipped cream dispensers[71, 72]. Inhalant abuse is associated with significant health risks, including acute toxic effects such as nausea, vomiting, headache, and loss of consciousness. Prolonged use can lead to severe neurological damage, organ damage, cognitive impairment, and even sudden death due to "sudden sniffing death syndrome" (SSDS), caused by

Table 6 The table displays the initial seed query for Hallucinogens and instances of the result from two datasets

Seed Keywords	Expanded Keywords
'LSD', 'Ayahuasca', 'Mushrooms', 'PCP', 'Acid', 'Mescaline', 'Psilocybin', 'Salvia'	'Ketamine', 'Khat', 'Kratom', 'SalviaDivinorum', 'Synthetic-Cathinones', 'Aya', 'Dimitri', 'Rogan', 'Jet', 'K', 'K-Hole', 'Kay', 'SpecialK', 'PizzaTopping', 'Shrooms', 'Magic Mushrooms', 'superman', 'SuperAcid', 'Kat', 'Qat', 'Ithang', 'Flakka', 'Kahyam', 'Ketum', 'Thom', 'Blotter', 'Dots', 'SugarCubes', 'Cactus', 'Mescal', 'Moon', 'Topi', 'Alice', 'Boomers', 'Caps', 'angel', 'Dust', 'Lucy', 'experience', 'trip', 'depression', 'suicide', 'near-death', 'mental'

fatal cardiac arrhythmias[73, 74]. Inhalant abuse is a significant public health concern, particularly among adolescents, due to the easy accessibility and low cost of these substances.

To recognize and keep track of the changing street names and related terms for inhalants, we utilized widely known scientific inhalant-related phrases as seed keywords for the DQE algorithm. We input the subsequent seed keywords into the DQE algorithm: "Amyl," "Nitrate," "Isobutyl," "Nitrous" and "Oxide" (refer to Table 7).We conducted in-depth experiments on two subreddits, r/Drugs, and r/Opiates, to showcase illustrative cases where pertinent terms and street names were effectively identified and tracked. An interesting case study of Inhalants is witnessed when using the keywords "Butane" and "huff." Butane, a highly flammable hydrocarbon gas, is sometimes misused as an inhalant for its psychoactive effects. This dangerous practice involves intentionally inhaling the vaporized butane to experience a temporary high, often characterized by feelings of euphoria, dizziness, and a sense of detachment. Butane is commonly found in products like lighter fluid, aerosol sprays, and portable gas stoves. Some users may directly inhale, sniff, or huff butane fumes from a container or a soaked cloth held over the mouth and nose. It is essential to note that using butane as an inhalant is extremely dangerous and can result in severe health consequences or even death. Furthermore, we successfully identified a multitude of dynamic slang names for Inhalants, such as "Amys," "Pearls," "Poppers," "Quicksilver," "Rush," and"Snappers"(see Table 7 for more examples).

Table 7 The table displays the initial seed query for Inhalants and instances of the result from two datasets

Seed Keywords	Expanded Keywords
'Amyl', 'Nitrate', 'Isobutyl', 'Nitrous', 'Oxide'	'Ames', 'Amies', 'Amys', 'glue', 'toxic', 'vomit', 'death', 'Pearls', 'Poppers', 'Bolt', 'Bullet', 'Climax', 'Hardware', 'LockerRoom', 'Poppers', 'Quicksilver', 'Rush', 'Snappers', 'Thrust', 'BuzzBomb', 'HippieCrack', 'LaughingGas', 'Whippets', 'huff', 'sniff', 'snort', 'bagging', 'butane', 'deodorant, 'coma'

Narcotics: also known as opioids or opiates, are a class of psychoactive substances that primarily act on the opioid receptors in the brain, producing pain relief, sedation, and a sense of euphoria[75]. Commonly used narcotics include morphine, codeine, oxycodone, hydrocodone, and the illicit drug heroin[76]. The use of narcotics can lead to a variety of short-term effects, including pain relief, drowsiness, constipation, and respiratory depression[77]. While narcotics can be highly effective for managing acute and chronic pain, they also pose significant risks, such as addiction, tolerance, dependence, and overdose[78]. The misuse of prescribed and illicit opioids have contributed to a global opioid crisis, with increasing rates of addiction, overdose deaths, and public health concerns[79].

To detect the evolving slang names and related terms for Narcotics, we used widely recognized Narcotics-associated phrases as seed keywords in the DQE algorithm. The following seed keywords were input: ”Buprenorphine,” ”Codeine,” ”Fentanyl,” ”Hydrocodone,” ”Hydromorphone,” ”Meperidine,” ”Methadone,” ”Morphine,” ”Oxycodone,” ”Oxymorphone,” ”Propoxyphene,” ”Suboxone,” ”Subutex” and ”Heroin,”(refer to Table 8). We performed extensive experiments on two subreddits, r/Drugs, and r/Opiates, illustrating various situations where pertinent terms and slang names were effectively identified and monitored. Some of the most identified pertinent keywords were ”alcohol” and ”addiction.” Combining opioids with alcohol is a dangerous practice that can lead to severe health risks and even death. Unfortunately, some individuals combine opioids and alcohol to amplify the euphoric or sedative effects of each substance, seeking a more intense high or a deeper state of relaxation. Both opioids and alcohol are central nervous system (CNS) depressants, which means they slow down brain function and can impair cognitive abilities, motor skills, and respiratory function. When used together, these substances can have additive or synergistic effects, resulting in intensified and potentially life-threatening consequences. In regard to detecting the evolving Narcotic drug names, we successfully identified many keywords such as ”Oxy,” ”Cody,” ”Oxycet,” ”Oxycotton,” and ”Ozone” (see table 8 for more examples).

Table 8 The table displays the initial seed query for Narcotics and instances of the result from two datasets

Seed Keywords	Expanded Keywords
’Buprenorphine’, ’Codeine’, ’Fentanyl’, ’Hydrocodone’, ’Hydromorphone’, ’Meperidine’, ’Methadone’, ’Morphine’, ’Oxycodone’, ’Oxymorphone’, ’Propoxyphene’, ’Suboxone’, ’Subutex’, ’Heroin’	’Oxy’, ’Oxycet’, ’Oxycotton’, ’Ozone’, ’Roxy’, ’Lortab’, ’Norco’, ’Vicodin’, ’Dilaudid’, ’Exalgo’, ’Demerol’, ’Dolophine’, ’Methadose’, ’Duramorph’, ’OxyContin’, ’Percocet’, ’Opana’, ’Darvocet’, ’Darvon’, ’Ultram’, ’Big Whites’, ’Buse’, ’SmallWhites’, ’Sobos’, ’Stops’, ’Strips’, ’Cody’, ’CaptainCody’, ’Schoolboy’, ’Sizzurp’, ’Apache’, ’TNT’, ’Bananas’, ’Fluff’, ’Hydros’, ’Tabs’,’Amidone’, ’Dollies’, ’Dolls’, ’Fizzies’, ’GodsDrug’, ’Morpho’, ’WhiteStuff’, ’Berries’, ’Blues’, ’Blueberries’, ’Rims’, ’Tires’, Octagons’, ’StopSign’, ’alcohol’, ’addiction’, ’addictive’, ’stress’, ’depression’, ’suicide’

Steroids: , or more specifically, anabolic-androgenic steroids (AAS), are a class of synthetic substances that are structurally related to the naturally occurring male sex hormone, testosterone[80]. AAS are commonly used to promote muscle growth, enhance athletic performance, and improve physical appearance[81]. While the use of steroids can result in increased muscle mass and strength, their misuse is associated with numerous adverse effects on physical and psychological health[82]. Potential side effects include cardiovascular complications, liver damage, hormonal imbalances, psychiatric disorders, and increased risk of infection due to needle sharing among users[83]. The non-medical use of AAS is considered a major public health concern, particularly among adolescents and young adults, due to the potential for long-lasting health consequences.

We employed widely recognized steroid-related terms as seed keywords for the DQE algorithm to detect the evolving slang names for these drugs and pinpoint the pertinent terms. Table 9 illustrates the used seed words "Steroid," "Nandrolone," and "Testosterone on two subreddits r/Drugs and r/Opiates. We showcase example scenarios that demonstrate the detection of pertinent terms and slang names. For instance, the expanded keywords "pain" and "opioid" were highly associated with the mentioned seed words. We find out that steroids can be combined with painkillers. Unfortunately, individuals who experience pain or inflammation from intense workouts or injuries may combine steroids with painkillers, such as nonsteroidal anti-inflammatory drugs (NSAIDs) or opioids. This can lead to increased health risks, particularly regarding liver and kidney function. Those individuals seek specific effects or attempt to mitigate side effects. However, combining steroids with other substances can increase the risk of adverse reactions and potential health problems. It is essential to understand that combining steroids with other drugs can pose serious risks to health and well-being. We also were able to identify a few other slang words for Steroids, such as "Arnolds," "roids," and "juice"(see table 9 for more examples). Compared to other categories, there were fewer expanded keywords in this category, indicating that steroids are not discussed as extensively as other drug topics.

Table 9 The table displays the initial seed query for Steroids and instances of the result from two datasets

Seed Keywords	Expanded Keywords
'Steroid', 'Nandrolone', 'Testosterone'	'Arnolds', 'Juice', 'MuscleBuilder', 'pumper', 'roids', 'stackers', 'GymCandy', 'WeightGainer', pain', 'opioid', 'painkiller', 'muscle', 'performance', 'stamina'

Stimulants: are a class of psychoactive substances that enhance alertness, attention, and energy by increasing the activity of certain neurotransmitters in the brain, such as dopamine and norepinephrine[84]. Common stimulants include amphetamines (e.g., Adderall), methamphetamine, methylphenidate (e.g., Ritalin), and cocaine[85]. Generally, the effects of stimulants include increased wakefulness, focus, motivation, and euphoria, as well as appetite suppression and increased heart rate and blood pressure[86]. While stimulants can be medically beneficial for the treatment of conditions such as attention deficit hyperactivity disorder (ADHD) and narcolepsy[87], their misuse can lead to a range of adverse effects and complications, including addiction, cardiovascular events, psychiatric disturbances, and neurotoxicity[88].

We utilized well-known stimulant-associated phrases as seed keywords in the DQE algorithm to identify the emerging slang names for these substances and accurately capture the relevant terms. Table 10 displays the seed words "Amphetamine," "Antidepressants," "Methylphenidate," "Cocaine," "Methamphetamine," "Adderall," "Dexedrine," "Paxil," "Prozac," "Zoloft," "Phentermine," "Adipex," "Concerta" and "Ritalin" used on two subreddits, r/Drugs, and r/Opiates. We present illustrative examples that highlight the successful detection of significant terms and evolving slang names. The most weighted keywords findings were the key terms "MDMA" and "Kratom". Sadly, some individuals combine MDMA (3,4-methylenedioxymethamphetamine), a psychoactive substance commonly known as ecstasy or molly, with kratom, a natural plant with opioid-like properties, is not recommended due to the potential for harmful interactions and increased health risks. Those individuals may believe that combining the two substances will produce a more intense or enjoyable experience by combining the euphoric and empathogenic effects of MDMA with the stimulant or sedative effects of kratom. However, the combination of these two substances can lead to unpredictable and potentially dangerous effects. It is important to avoid combining MDMA and kratom due to the potential risks and lack of research on their interaction. Regarding the detection of street/slang keywords, there were more extracted keywords than other categories, and our interpretation of that is that most stimulants are used in association with other drugs. Here are examples of the most used words "candyflipping," "Ecstasy," and "Molly" (refer to table 10 for more instances).

Table 10 The table displays the initial seed query for Stimulants and instances of the result from two datasets

Seed Keywords	Expanded Keywords
'Amphetamine', 'Antidepressants', 'Methylphenidate', 'Cocaine', 'Methamphetamine"Adderall', 'Dexedrine', 'Paxil', 'Prozac', 'Zoloft', 'Phentermine', 'Adipex', 'Concerta', 'Ritalin'	'MDMA', 'Ecstasy', 'Molly', 'AuntNora', 'Batman', 'Candy', 'candyflipping', 'Colombia', 'Crack', 'Pearl', 'Powder', 'Snow', 'Stardust', 'Stash', 'Speedball', 'Chalk', 'Cookies', 'Crank', 'Crystal', 'CrystalMeth', 'Ice', 'Meth', 'Speed', 'Trash', 'Addies', 'Skippy', 'Dice', 'Garbage', 'Grit', 'Hail', 'Nuggets', 'Eve', 'Peace', 'Rolls', 'Smartees', 'Kratom', 'dance', 'sex', 'sleep', 'insomnia', 'depressed', 'water', 'suicide'

5.1.2 A specific case study on one drug only (Fentanyl)

We applied the modified DQE algorithm to general drug categories, and it showed success even though there was noise (unrelated words or words from other drugs' categories) in the extracted words. One of the reasons that there is a lot of noise in the expanded queries is that we applied the algorithm to general drug categories, which include varieties of substances for each category as shown previously. Therefore, we designed a case study for this specific case, and we chose only one drug for this experiment. We conducted our experiment on Fentanyl, which is a significant contributor to the opioid crisis due to its increased prevalence, leading to a substantial rise in overdose deaths in the United States and other countries.

Fentanyl: is a powerful synthetic opioid analgesic that is approximately 50 to 100 times more potent than morphine, and it is primarily used for the management of severe pain, such as in cancer patients or during surgical procedures[89]. Due to its potency and rapid onset of action, fentanyl has become increasingly popular as a drug of abuse and a significant contributor to the ongoing opioid crisis[90]. Fentanyl and its analogs have been implicated in a growing number of overdose deaths, as they are often mixed with other drugs, such as heroin, cocaine, or counterfeit prescription pills, without the user's knowledge[91]. The misuse of fentanyl poses serious risks, including respiratory depression, unconsciousness, and overdose, which can be fatal[92].

To identify and monitor relevant, evolving street names for Fentanyl, we utilized well-known Fentanyl terms as seed words within the DQE algorithm. In Table11, seed words included "Fentanyl," "Fent," and "Fenty". We performed experiments on two subreddits, r/Drugs, and r/Opiates, demonstrating examples that involved identifying significant terms and street names. An example of pinpointing related terms to "Fentanyl" is the expanded keywords "addiction, "addictive," "euphoria," and "horrible". Fentanyl is addictive because it binds to specific receptors in the brain, known as mu-opioid receptors. These receptors are responsible for the body's natural pain-relieving response but also play a role in the reward system of the brain. When fentanyl binds to these receptors, it activates the reward system, which can cause feelings of pleasure and euphoria. However, over time, the brain can become desensitized to the effects of fentanyl, and users may need to take higher doses to achieve the same level of euphoria. This can lead to tolerance, where the body becomes accustomed to the drug and requires higher and higher doses to achieve the desired effects. The explanation why the drug is "horrible is because fentanyl withdrawal can be very uncomfortable and even dangerous, with symptoms including nausea, vomiting, diarrhea, muscle aches, sweating, anxiety, and insomnia. It also can cause respiratory depression, which can lead to coma or death. It is important to seek professional help if someone is struggling with a fentanyl addiction. Finally, many evolving fentanyl slang words were captured, such as "ChinaWhite," "Apache," and "Chinas" (see table 11 for detailed examples). The noise in the extended query was present such as "mean," "case," "fat," and "problem". This corroborates our findings that the DQE algorithm is an asset and can be utilized jointly as one of the modules in PRISTINE.

Table 11 The table displays the initial seed query for Fentanyl and examples of the result from two datasets

Seed Keywords	Expanded Keywords
'Fentanyl', 'Fent', 'Fenty'	'morphine', 'injection', 'overdoses', 'overdose', 'OD', 'heroin', 'cocaine', 'euphoria', 'nausea', 'confusion', 'addiction', 'constipation', 'patch', 'opiate ', 'Apache', 'Jackpot', 'Dragon', 'Chi', 'Chinatown', 'Chi-town', 'Fire', 'Butter', 'China-Girl', 'ChinaWhite', 'chinas', 'Indochina', 'echinacea', 'Chinawhite', 'chinashithole', 'china-fent', 'snortable', 'depression', 'snorted', 'brain', 'hydros', 'hell', 'recovery', 'methoxy-acetylfentanyl', 'propionylfentanyl', 'pharoahfentanyl', 'fent-roin', 'fentynol', 'acrylfentanyl', 'suicide', Sublimaze, 'Actiq', 'smoke', 'horrible', 'alcohol'

5.2 Exploring the efficacy of PRISTINE in categorizing Subreddits

In this subsection, we embark on a comprehensive examination of the PRISTINE framework, which adeptly classifies subreddits into seven distinct drug classes. To demonstrate the effectiveness of PRISTINE in categorizing Reddit posts, we present real-world examples of subreddits from each drug class while maintaining anonymity (see table 12 for the examples of this study). Our case studies involve numerous random Reddit posts submitted to PRISTINE for classification, with actual anonymized examples showcased for illustrative purposes. Through this analysis of PRISTINE's performance, we aim to offer insights into the algorithm's efficacy, highlighting its potential to augment user experience on Reddit. This evaluation serves as a demonstration of PRISTINE's capabilities in addressing the intricate task of subreddit classification.

In the table below (table 12), we present a series of actual Reddit posts alongside their true labels and the classifications produced by our framework. This comparison provides a representative illustration of the framework's performance in assigning accurate labels to subreddit content across various drug categories. We notice that PRISTINE correctly classifies most of the subreddit posts, but our concern is the misclassified ones. For example, the actual label of post #12 is Stimulant because it apparently discusses how MDMA is mixed with orange juice. However, PRISTINE misclassified it as a Steroid. We notice that PRISTINE does not rely entirely on the DQE algorithm but also on the context of the word embeddings. Nevertheless, our framework demonstrates good performance, and there is room for improvement.

Table 12 PRISTINE's Performance in classifying Subreddit Posts by Drug Classes. A= Actual label, P= Predicted label, H= Hallucinations, C= Cannabis, D= Depressants, I= Inhalants, N= Narcotics, Sd= Steroids, St= Stimulants

#	A	P	Subreddit comement
1	H	H	"@No I can say that's never happened with MDMA/MDA, I've had some doozies with other shit though..... mushrooms and LSD ive definitely had some learning experiences on my own"
2	H	C	"@I can promise you that's not true, because your body will almost definitely be telling you to slow down. I'm the same, I smoke lots of hash and binge use ketamine (so I ill do 3 grams of strong stuff in two days easily) and I can drink a lot and sometimes use Valium but I can tell it's not good for me. Luckily opioids (other than Kratom which I love and use frequently) never really caught my attraction. For sure mushrooms and the psyche I've tried are the best experiences by far. But ye ye wana try cut down on that shit man, you'll have to stop at some point so might as well do it sooner than later."
3	C	C	"@Try not smoking right before you go to sleep. Cannabis effects your REM sleep (like alcohol does), which is probably why you feel foggy in the morning. The effect on REM sleep is greatly reduced if you don't smoke 3 hours before you fall asleep. I usually don't smoke 2 hours before and I don't have any fog in the morning. Sometimes on the weekend I don't follow that rule and it shows."
4	D	D	"@I'd take another Ativan before mixing. Plus, a benadryl sleep for me is a weird, unfulfilling sleep. Mixing generally not good imo. "
5	St	D	"@Take a little bit of adderall. 5-10mg and drink/smoke a bit. Definitely don't take Xanax at a rave."
6	D	D	"@Ativan is almost same as xanex. The diffeence is ativan is long acting and xanex is immediate. U nearly took 15 mgs of anxiety medication at once. Id say 12-13mgs. "
7	H	I	"@Very interesting. I often find I get the most hyper realistic hallucinations with dxm compared to other hallucinogens especially when combined with nitrous. Insanely realistic. "
8	I	I	"@Poppers lower your blood pressure. Normally, this is not problematic, but it could be if you already have low blood pressure, or if you're taking another drug that also lowers blood pressure. Viagra, for instance, also lowers blood pressure and should not be used with poppers."
9	N	N	"@I've recently been getting a morphine heavy fent cut mix the pins and needles in my hands after the shot almost hurt most times but the fent usually evens me out and sends me into a good nod. "
10	N	N	"@I just had 4 hydros and some codeine set up to take and I backed out last second. Proud of myself but I'm going to relapse "
11	Sd	Sd	"@Yeah that's why I said typically. I actually first heard it referring to H back in the 00's but more recently almost exclusively it's roids."
12	St	Sd	"@dose out your mdma...put it into containers/bottles of orange juice...get in festival and slam the bottle of OJ"
13	St	St	"@Amphetamines constrict blood vessels, I actually had this issue today..."
14	N	St	"@I found my younger cousin twice this year in the house we were living in together. The second time he was long dead from a fentynal overdose. Dear God please don't do this to the ones you love. If you feel you want to use cocaine and no one will stop you then please invest in a test kit. They're super cheap and can absolutely save your life.""

6 Conclusion

In conclusion, this study builds on previous work aimed at addressing the drug abuse epidemic by extending the PRISTINE framework to investigate opioid crisis trends on an expanded dataset from two subreddits. The study demonstrates the effectiveness of the DQE algorithm in identifying drug-related and evolving drug terms and provides comprehensive case studies for seven drug categories. The study also includes a new analysis that shows the strong performance of PRISTINE in categorizing subreddits into fine-grained drug classes. Through the use of extensive experiments, the study demonstrates the overall effectiveness of the proposed framework in mitigating the opioid crisis. These findings highlight the potential of utilizing data from social media platforms such as Reddit to gain insights into drug abuse trends and inform efforts to combat this ongoing public health crisis.

References

[1] Wide-ranging online data for epidemiologic research (WONDER. CDC, National Center for Health Statistics, Atlanta, GA. Available at http://wonder.cdc.gov/. http://wonder.cdc.gov.

[2] Wadekar, A.S.: A psychosocial approach to predicting substance use disorder (sud) among adolescents. In: 2020 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), pp. 819–826 (2020). IEEE

[3] Tabar, M., Park, H., Winkler, S., Lee, D., Barman-Adhikari, A., Yadav, A.: Identifying homeless youth at-risk of substance use disorder: Data-driven insights for policymakers. In: Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 3092–3100 (2020)

[4] Singh, A.K., Wu, D.: Sentiment analysis on substance use disorder (sud) tweets before and during covid-19 pandemic. In: International Conference on Human-Computer Interaction, pp. 608–614 (2021). Springer

[5] Sequeira, R., Gayen, A., Ganguly, N., Dandapat, S.K., Chandra, J.: A large-scale study of the twitter follower network to characterize the spread of prescription drug abuse tweets. IEEE Transactions on Computational Social Systems **6**(6), 1232–1244 (2019)

[6] Lossio-Ventura, J.A., Bian, J.: An inside look at the opioid crisis over twitter. In: 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 1496–1499 (2018). IEEE

[7] Saifuddin, K.M., Akbas, E., Khanov, M., Beaman, J.: Effects of covid-19

on individuals in opioid addiction recovery. In: 2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA), pp. 1333–1340 (2021). IEEE

[8] Lavertu, A., Hamamsy, T.C., Altman, R.B.: Monitoring the opioid epidemic via social media discussions. medRxiv (2021)

[9] Buntain, C., Golbeck, J.: This is your twitter on drugs: Any questions? In: Proceedings of the 24th International Conference on World Wide Web, pp. 777–782 (2015)

[10] Barenholtz, E., Fitzgerald, N.D., Hahn, W.E.: Machine-learning approaches to substance-abuse research: Emerging trends and their implications. Current opinion in psychiatry **33**(4), 334–342 (2020)

[11] Gong, H., Qian, C., Wang, Y., Yang, J., Yi, S., Xu, Z.: Opioid abuse prediction based on multi-output support vector regression. In: Proceedings of the 2019 4th International Conference on Machine Learning Technologies, pp. 36–41 (2019)

[12] McKim, K.G., Mai, C., Hess, D., Niu, S.: Investigating drug addiction discourse on youtube. In: Companion Publication of the 2021 Conference on Computer Supported Cooperative Work and Social Computing, pp. 130–134 (2021)

[13] Fan, Y., Zhang, Y., Ye, Y., Li, X., Zheng, W.: Social media for opioid addiction epidemiology: Automatic detection of opioid addicts from twitter and case studies. In: Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, pp. 1259–1267 (2017)

[14] Soni, D., Ghanem, T., Gomaa, B., Schommer, J.: Leveraging twitter and neo4j to study the public use of opioids in the usa. In: Proceedings of the 2nd Joint International Workshop on Graph Data Management Experiences & Systems (GRADES) and Network Data Analytics (NDA), pp. 1–5 (2019)

[15] Hu, H., Phan, N., Ye, X., Jin, R., Ding, K., Dou, D., Vo, H.T.: Drugtracker: A community-focused drug abuse monitoring and supporting system using social media and geospatial data (demo paper). In: Proceedings of the 27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, pp. 564–567 (2019)

[16] Yang, X., Luo, J.: Tracking illicit drug dealing and abuse on instagram using multimodal analysis. ACM Transactions on Intelligent Systems and Technology (TIST) **8**(4), 1–15 (2017)

[17] Alhamadani, A., Sarkar, S., Alkulaib, L., Lu, C.-T.: Pristine: Semi-supervised deep learning opioid crisis detection on reddit. In: 2022 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), pp. 444–453 (2022). IEEE

[18] Nasralah, T., El-Gayar, O., Wang, Y., *et al.*: Social media text mining framework for drug abuse: development and validation study with an opioid crisis case analysis. Journal of medical Internet research **22**(8), 18350 (2020)

[19] Pandrekar, S., Chen, X., Gopalkrishna, G., Srivastava, A., Saltz, M., Saltz, J., Wang, F.: Social media based analysis of opioid epidemic using reddit. In: AMIA Annual Symposium Proceedings, vol. 2018, p. 867 (2018). American Medical Informatics Association

[20] Bunting, A.M., Frank, D., Arshonsky, J., Bragg, M.A., Friedman, S.R., Krawczyk, N.: Socially-supportive norms and mutual aid of people who use opioids: An analysis of reddit during the initial covid-19 pandemic. Drug and alcohol dependence **222**, 108672 (2021)

[21] Lossio-Ventura, J.A., Jonquet, C., Roche, M., Teisseire, M.: Biotex: A system for biomedical terminology extraction, ranking, and validation. In: ISWC: International Semantic Web Conference, pp. 157–160 (2014)

[22] Zhang, Y., Fan, Y., Ye, Y., Li, X., Winstanley, E.L.: Utilizing social media to combat opioid addiction epidemic: automatic detection of opioid users from twitter. In: Workshops at the Thirty-second AAAI Conference on Artificial Intelligence (2018)

[23] Sarker, A., Gonzalez-Hernandez, G., Ruan, Y., Perrone, J.: Machine learning and natural language processing for geolocation-centric monitoring and characterization of opioid-related social media chatter. JAMA network open **2**(11), 1914672–1914672 (2019)

[24] Hu, H., Phan, N., Chun, S.A., Geller, J., Vo, H., Ye, X., Jin, R., Ding, K., Kenne, D., Dou, D.: An insight analysis and detection of drug-abuse risk behavior on twitter with self-taught deep learning. Computational Social Networks **6**(1), 1–19 (2019)

[25] Saifuddin, K.M., Islam, M.I.K., Akbas, E.: Drug abuse detection in twitter-sphere: Graph-based approach. In: 2021 IEEE International Conference on Big Data (Big Data), pp. 4136–4145 (2021). IEEE

[26] Dey, P., Zhai, C.: Fine grained categorization of drug usage tweets. In: Social Computing and Social Media: Design, User Experience and Impact: 14th International Conference, SCSM 2022, Held as Part of the 24th HCI International Conference, HCII 2022, Virtual Event, June 26–July 1, 2022,

Proceedings, Part I, pp. 267–280 (2022). Springer

[27] Chancellor, S., Nitzburg, G., Hu, A., Zampieri, F., De Choudhury, M.: Discovering alternative treatments for opioid use recovery using social media. In: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1–15 (2019)

[28] Jha, D., La Marca, S.R., Singh, R.: Identifying and characterizing opioid addiction states using social media posts. In: 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 913–918 (2021). IEEE

[29] Alhamadani, A., Sarkar, S., Alkulaib, L., Lu, C.-T.: Dod-explainer: Explainable drug overdose deaths predictor from crime and socioeconomic data. In: 2022 IEEE International Conference on Big Data (Big Data), pp. 5163–5172 (2022). https://doi.org/10.1109/BigData55660.2022.10021054

[30] Islam, U.I., Haque, E., Alsalman, D., Islam, M.N., Moni, M.A., Sarker, I.H.: A machine learning model for predicting individual substance abuse with associated risk-factors. Annals of Data Science, 1–28 (2022)

[31] Kipf, T.N., Welling, M.: Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907 (2016)

[32] Yao, L., Mao, C., Luo, Y.: Graph convolutional networks for text classification. In: Proceedings of the AAAI Conference on Artificial Intelligence, vol. 33, pp. 7370–7377 (2019)

[33] Dan, L., Zhichang, Z., Hui, P., Ruirui, H.: Gcn with external knowledge for clinical event detection. In: Proceedings of the 20th Chinese National Conference on Computational Linguistics, pp. 1190–1201 (2021)

[34] Fu, K., Ji, T., Self, N., Chen, Z., Lu, C.-T.: A hierarchical attention graph convolutional network for traffic incident impact forecasting. In: 2021 IEEE International Conference on Big Data (Big Data), pp. 1619–1624 (2021). IEEE

[35] Guo, K., Hu, Y., Sun, Y., Qian, S., Gao, J., Yin, B.: Hierarchical graph convolution networks for traffic forecasting. In: Proceedings of the AAAI Conference on Artificial Intelligence, vol. 35, pp. 151–159 (2021)

[36] Zhao, L., Gao, Y., Ye, J., Chen, F., Ye, Y., Lu, C.-T., Ramakrishnan, N.: Spatio-temporal event forecasting using incremental multi-source feature learning. ACM Transactions on Knowledge Discovery from Data (TKDD) **16**(2), 1–28 (2021)

[37] Zhao, L., Chen, F., Dai, J., Hua, T., Lu, C.-T., Ramakrishnan, N.:

Unsupervised spatial event detection in targeted domains with applications to civil unrest modeling. PLOS ONE **9**(10), 110206 (2014). https://doi.org/10.1371/journal.pone.0110206

[38] Khandpur, R.P., Ji, T., Ning, Y., Zhao, L., Lu, C.-T., Smith, E.R., Adams, C., Ramakrishnan, N.: Determining relative airport threats from news and social media. In: Twenty-Ninth IAAI Conference (2017)

[39] Zhao, L., Sun, Q., Ye, J., Chen, F., Lu, C.-T., Ramakrishnan, N.: Multi-task learning for spatio-temporal event forecasting. In: Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1503–1512 (2015)

[40] Khandpur, R.P., Ji, T., Jan, S., Wang, G., Lu, C.-T., Ramakrishnan, N.: Crowdsourcing cybersecurity. In: Proceedings of the 2017 ACM on Conference on Information and Knowledge Management. ACM, ??? (2017). https://doi.org/10.1145/3132847.3132866. https://doi.org/10.1145%2F3132847.3132866

[41] Zulfiqar, O., Chang, Y.-C., Chen, P.-H., Fu, K., Lu, C.-T., Solnick, D., Li, Y.: Risecure: Metro incidents and threat detection using social media. In: 2020 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), pp. 531–535 (2020). https://doi.org/10.1109/ASONAM49781.2020.9381317

[42] Zhao, L., Chen, J., Chen, F., Jin, F., Wang, W., Lu, C.-T., Ramakrishnan, N.: Online flu epidemiological deep modeling on disease contact network. GeoInformatica **24**(2), 443–475 (2020). https://doi.org/10.1007/s10707-019-00376-9

[43] Chen, X.: Understanding spectral graph neural network. arXiv preprint arXiv:2012.06660 (2020)

[44] Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C., Philip, S.Y.: A comprehensive survey on graph neural networks. IEEE transactions on neural networks and learning systems **32**(1), 4–24 (2020)

[45] Hammond, D.K., Vandergheynst, P., Gribonval, R.: Wavelets on graphs via spectral graph theory. Applied and Computational Harmonic Analysis **30**(2), 129–150 (2011)

[46] Baumgartner, J., Zannettou, S., Keegan, B., Squire, M., Blackburn, J.: The pushshift reddit dataset. In: Proceedings of the International AAAI Conference on Web and Social Media, vol. 14, pp. 830–839 (2020)

[47] Schick, T., Schütze, H.: Bertram: Improved word embeddings have big impact on contextualized model performance. arXiv preprint

arXiv:1910.07181 (2019)

[48] Almeida, F., Xexéo, G.: Word embeddings: A survey. arXiv preprint arXiv:1901.09069 (2019)

[49] Aizawa, A.: An information-theoretic perspective of tf–idf measures. Information Processing & Management **39**(1), 45–65 (2003)

[50] Mikolov, T., Sutskever, I., Chen, K., Corrado, G.S., Dean, J.: Distributed representations of words and phrases and their compositionality. Advances in neural information processing systems **26** (2013)

[51] Pennington, J., Socher, R., Manning, C.D.: Glove: Global vectors for word representation. In: Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 1532–1543 (2014)

[52] Bojanowski, P., Grave, E., Joulin, A., Mikolov, T.: Enriching word vectors with subword information. Transactions of the association for computational linguistics **5**, 135–146 (2017)

[53] Devlin, J., Chang, M.-W., Lee, K., Toutanova, K.: Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018)

[54] Reimers, N., Gurevych, I.: Sentence-bert: Sentence embeddings using siamese bert-networks. arXiv preprint arXiv:1908.10084 (2019)

[55] Volkow, N.D., Baler, R.D., Compton, W.M., Weiss, S.R.: Adverse health effects of marijuana use. New England Journal of Medicine **370**(23), 2219–2227 (2014)

[56] Moore, T.H., Zammit, S., Lingford-Hughes, A., Barnes, T.R., Jones, P.B., Burke, M., Lewis, G.: Cannabis use and risk of psychotic or affective mental health outcomes: a systematic review. The Lancet **370**(9584), 319–328 (2007)

[57] Whiting, P.F., Wolff, R.F., Deshpande, S., Di Nisio, M., Duffy, S., Hernandez, A.V., Keurentjes, J.C., Lang, S., Misso, K., Ryder, S., *et al.*: Cannabinoids for medical use: a systematic review and meta-analysis. Jama **313**(24), 2456–2473 (2015)

[58] Kollins, S.H., Schoenfelder, E.N., English, J.S., Holdaway, A., Van Voorhees, E., O'Brien, B.R., Dew, R., Chrisman, A.K.: An exploratory study of the combined effects of orally administered methylphenidate and delta-9-tetrahydrocannabinol (thc) on cardiovascular function, subjective effects, and performance in healthy adults. Journal

of substance abuse treatment **48**(1), 96–103 (2015)

[59] Julien, R.M.: A Primer of Drug Action: A Concise Nontechnical Guide to the Actions, Uses, and Side Effects of Psychoactive Drugs, Revised and Updated. Holt Paperbacks, ??? (2013)

[60] Ries, R.K., Fiellin, D.A., Miller, S.C., Saitz, R.: The ASAM Principles of Addiction Medicine. Lippincott Williams & Wilkins, ??? (2014)

[61] Mintzer, M.Z., Griffiths, R.: Alcohol and triazolam: differential effects on memory, psychomotor performance and subjective ratings of effects. Behavioural Pharmacology **13**(8), 653–658 (2002)

[62] O'Brien, C.P.: Benzodiazepine use, abuse, and dependence. J Clin Psychiatry **66**(Suppl 2), 28–33 (2005)

[63] Baldwin, D.S., Anderson, I.M., Nutt, D.J., Allgulander, C., Bandelow, B., den Boer, J.A., Christmas, D.M., Davies, S., Fineberg, N., Lidbetter, N., *et al.*: Evidence-based pharmacological treatment of anxiety disorders, post-traumatic stress disorder and obsessive-compulsive disorder: a revision of the 2005 guidelines from the british association for psychopharmacology. Journal of Psychopharmacology **28**(5), 403–439 (2014)

[64] Nichols, D.E.: Psychedelics. Pharmacological reviews **68**(2), 264–355 (2016)

[65] Tylš, F., Páleníček, T., Horáček, J.: Psilocybin–summary of knowledge and new perspectives. European Neuropsychopharmacology **24**(3), 342–356 (2014)

[66] Vollenweider, F.X., Kometer, M.: The neurobiology of psychedelic drugs: implications for the treatment of mood disorders. Nature Reviews Neuroscience **11**(9), 642–651 (2010)

[67] Strassman, R.J.: Adverse reactions to psychedelic drugs. a review of the literature. The Journal of nervous and mental disease **172**(10), 577–595 (1984)

[68] Johnson, M.W., Richards, W.A., Griffiths, R.R.: Human hallucinogen research: guidelines for safety. Journal of psychopharmacology **22**(6), 603–620 (2008)

[69] Carhart-Harris, R.L., Goodwin, G.M.: The therapeutic potential of psychedelic drugs: past, present, and future. Neuropsychopharmacology **42**(11), 2105–2113 (2017)

[70] González, D., Riba, J., Bouso, J.C., Gómez-Jarabo, G., Barbanoj, M.J.: Pattern of use and subjective effects of salvia divinorum among recreational users. Drug and alcohol dependence **85**(2), 157–162 (2006)

[71] Balster, R.L.: Neural basis of inhalant abuse. Drug and alcohol dependence **51**(1-2), 207–214 (1998)

[72] Garland, E.L., Howard, M.O.: Volatile substance misuse: clinical considerations, neuropsychopharmacology and potential role of pharmacotherapy in management. CNS drugs **26**, 927–935 (2012)

[73] Anderson, C.E., Loomis, G.A.: Recognition and prevention of inhalant abuse. American family physician **68**(5), 869–874 (2003)

[74] Lubman, D., Yücel, M., Lawrence, A.: Inhalant abuse among adolescents: neurobiological considerations. British journal of pharmacology **154**(2), 316–326 (2008)

[75] Benyamin, R., Trescot, A.M., Datta, S., Buenaventura, R.M., Adlaka, R., Sehgal, N., Glaser, S.E., Vallejo, R.: Opioid complications and side effects. Pain physician **11**(2S), 105 (2008)

[76] Inturrisi, C.E.: Clinical pharmacology of opioids for pain. The Clinical journal of pain **18**(4), 3–13 (2002)

[77] Kalso, E., Edwards, J.E., Moore, R.A., McQuay, H.J.: Opioids in chronic non-cancer pain: systematic review of efficacy and safety. Pain **112**(3), 372–380 (2004)

[78] Volkow, N.D., McLellan, A.T.: Opioid abuse in chronic pain—misconceptions and mitigation strategies. New England Journal of Medicine **374**(13), 1253–1263 (2016)

[79] Dowell, D., Arias, E., Kochanek, K., Anderson, R., Guy, G.P., Losby, J.L., Baldwin, G.: Contribution of opioid-involved poisoning to the change in life expectancy in the united states, 2000-2015. Jama **318**(11), 1065–1067 (2017)

[80] Basaria, S.: Androgen abuse in athletes: detection and consequences. The Journal of Clinical Endocrinology & Metabolism **95**(4), 1533–1543 (2010)

[81] Kanayama, G., Hudson, J.I., Pope Jr, H.G.: Long-term psychiatric and medical consequences of anabolic–androgenic steroid abuse: A looming public health concern? Drug and alcohol dependence **98**(1-2), 1–12 (2008)

[82] Hartgens, F., Kuipers, H.: Effects of androgenic-anabolic steroids in athletes. Sports medicine **34**, 513–554 (2004)

[83] Sagoe, D., Molde, H., Andreassen, C.S., Torsheim, T., Pallesen, S.: The global epidemiology of anabolic-androgenic steroid use: a meta-analysis and meta-regression analysis. Annals of epidemiology **24**(5), 383–398 (2014)

[84] Rothman, R.B., Baumann, M.H.: Monoamine transporters and psychostimulant drugs. European journal of pharmacology **479**(1-3), 23–40 (2003)

[85] Iversen, L.: Speed, Ecstasy, Ritalin: The Science of Amphetamines. Oxford University Press, ??? (2008)

[86] Volkow, N.D., Wang, G.-J., Fowler, J.S., Ding, Y.-S.: Imaging the effects of methylphenidate on brain dopamine: new model on its therapeutic actions for attention-deficit/hyperactivity disorder. Biological psychiatry **57**(11), 1410–1415 (2005)

[87] Wigal, S.B.: Efficacy and safety limitations of attention-deficit hyperactivity disorder pharmacotherapy in children and adults. CNS drugs **23**, 21–31 (2009)

[88] Volkow, N.D., Fowler, J.S., Wang, G.-J., *et al.*: The addicted human brain: insights from imaging studies. The Journal of clinical investigation **111**(10), 1444–1451 (2003)

[89] Stanley, T.H.: The fentanyl story. The Journal of Pain **15**(12), 1215–1226 (2014)

[90] Ciccarone, D.: The triple wave epidemic: supply and demand drivers of the us opioid overdose crisis. The International journal on drug policy **71**, 183 (2019)

[91] Gladden, R.M., O'Donnell, J., Mattson, C.L., Seth, P.: Changes in opioid-involved overdose deaths by opioid type and presence of benzodiazepines, cocaine, and methamphetamine—25 states, july–december 2017 to january–june 2018. Morbidity and mortality weekly report **68**(34), 737 (2019)

[92] Volpe, D.A., Tobin, G.A.M., Mellon, R.D., Katki, A.G., Parker, R.J., Colatsky, T., Kropp, T.J., Verbois, S.L.: Uniform assessment and ranking of opioid mu receptor binding constants for selected opioid drugs. Regulatory Toxicology and Pharmacology **59**(3), 385–390 (2011)