Sentiment Analysis of Drugs related Post Impacting the Society Healthcare

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Abstract: People in this digital age spend their important time on social media for diverse application. Generally, social media addiction bound individuals to discuss everything on this platform, because of which their personal and uncultured words used in communication, affect the cultured society. Individuals from different fields discuss about their domain of interest. Sportsperson discuss their sports, doctors discuss medicine, teachers discuss their subject, similarly alcoholic or addicted person discuss on drugs. Drug related tweets are normally visible in social media communication for different discussion. Analyzing these tweets maybe in positive or negative sense will help understand the social impact of these drug related posts in society. Due to the higher drawback of such words, researchers continue finding the spreading of drug related post and their impact on society. Positive sentiment actually means drug advertisement or drug usage encouragement that will actually have NEGATIVE impact on society Pharmacists also compute the impact of these words for marketing of medicine. In this paper, we compute the negative impact on society through the use of drug associated post using sentiment analysis in different period of time for two prominent cities of India: a) Delhi: capital city creating the honored cultures society b) Bangalore: IT hub city of India.. We find Bangalore has slightly large contribution of 50.90% of positive sentiment drug related tweets compared to Delhi which has 49.10%. Thus Bangalore city tweets have slightly worse impact on society compared to Delhi.

Keyword: Drugs, Social Media, Twitter, Sentiment analysis, healthcare

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1. INTRODUCTION

Drug abuse and addiction, is a condition characterized by a self-destructive pattern of using a substance that leads to significant problems and distress, which may include tolerance to or withdrawal from the substance.. Drug use disorder is unfortunately quite common, affecting more than 8% of people in the United States at some point in their lives. People can abuse virtually any substance whose ingestion can result in a euphoric ("high") feeling.

Continuous posting of drug associated posts on social media may motivate the new comers for thinking about the drug use. Drug related post change the mental interest of intoxicating the society. Several researcher have been identifying the impact through drug associated post in diverse geographical region. Hashtags are most prevalent features of social platform. These hashtags deliver personalized feeds that may drive drug-sale posts directly to users who have expressed interest in them. This will expose vulnerable people to addictive drugs. So it is very important to find drug related post especially with positive sentiment as they perversely impact society. Research in sentiment analysis started in the early 2000s. Since then, several methods to analyze the opinions and emotions from online opinion sources (blogs, forums, or commercial websites) have been introduced. Nowadays a special interest has arisen on the social networks such as Twitter where people share their opinions about several topics such as drug abuse [1].

2. RELATED WORK

In their research Ming et. al discuss a framework to tackle the difficulty to filter the big data, especially identification of adverse drug reactions (ADRs) messages from social media. Author introduce LDA model as a dimension reduction technique to apply on various high-dimensional problems, and model the learning process [2]. Sarker et. al, in his data article developed data mining tools to collect the data from Twitter. They used drug name including their common misspelled forms as keywords for searching [3]. Pappal et. al developed a new classifications of data from social media for practical applications in the area of pharmacovigilance. [4].

Zhou et. al, in this paper, explore how images and text multimedia data extracted from social media can be used for discovering drug use patterns with respect to demographics. This data is extracted using face image analysis algorithms [5].

As per reports from the World Bank, risky behaviors are increasingly widespread globally and are a growing threat to individual health and society. In order to support and utilize this correlation, author investigate five risky behaviors: drinking, drug consumption, depression, eating disorder and sleep disorder. In this paper, Zhou et. al, utilize Instagram data to identify the correlation between these five risk behaviors and employ multi-task machine learning techniques for predicting the risk behaviors for the Instagram users [6]. Due to the potential challenges and combined efforts of all key stakeholders that overcome the difficulties, social media is a great tool for ADR reporting and a great platform for consumers and pharma-companies to discuss their opinions and experiences regarding the use of the medicinal product and devices. [7]. Tang et. al, in his paper, investigates deep neural network-based ADR recognition. Here deep neural network combines LSTM and conditional random fields for recognizing ADR from social media in medicine [8]. Yakushev et. al, in his work used social media data for analysis and modeling of drug usage. He employed dictionary of drug related key phrases and keywords to develop a model for predicting people in specified areas having different levels of drug addiction [9]. Ding et. al, in his paper, identifies drug abuse related posts using a topic modeling-based approach. In this approach hashtags are disambiguated using semantic word embedding [10]. Abdulahi et. al, examines the relationship between social network sites and health threat. It studies how facebook users suffer their privacy issue without understanding their risk in socializing [11]. Curtis et. al, in his work, shows concern of interpreting social media results with caution to study new medications shortly after licensure [12]. Author use social media to study opioid abuse and also build tools to extract information about opioid use in Twitter post[13]. In this paper, Kim et.al propose a framework for social media communication data for understanding problematic drug use phenomena [14]. This work identifies new and emerging drugs by developing different approaches to extract content from social networks using multi-disciplinary collaboration including computer scientists, health service providers, government/community services, mathematicians, public citizens and internet technical specialist. [15]. Phan et. al, in their study, presented a classification system for drug abuse related tweets. Their system validated the system on tweet dataset with 74.8% precision [16]. Omana et. al, in their paper developed application that used Support Vector Machine classification for identifying tweets that are either drug related or disease related. [17].

Jiang et. al used Twitter data for extracting potential drug effects using NLP and machine learning processing. They used Twitter text data for finding drug effect signals that supplement and/or complement other existing drug safety methods [18]. Bollegala et. al proposed a signal detection problem. In his paper, the author determined whether an event R is related to drug D from a given a social media post T [19]. Mahata et. al, in his paper studied the effectiveness of CNNs for personal medication from Twitter posts [20]. Paul et. al, in their work surveyed social media impact on public health by studying different research carried on this field. Their study was organized into three different sections. One section described recent progress in public health problems. The second section studied computational methods and third section was about social implications. [21]. Roy et. al, in this research, used image and text analytics for identifying social media posts related to illicit drug. For conducting experiments, Instagram dataset was collected that contained about 100K posts. Dataset was trained on CNN and Doc2Vec to identify drug related posts [22]. Sarker et. al, in their work investigated social media as a potential resource for analyzing abuse pattern of medication [23]. Segura et. al, presented a system to detect drug effects collected from user messages from a Spanish health website. [24]. Yu et. al, in their paper, applied supervised learning for extracting useful information about drugs from Twitter. For increasing the accuracy of classification, a spam filter and a preprocessing procedure were developed. To test for increasing accuracy, experiments were performed on streamed tweets. The tweets were collected from Twitter in real time continuously for 48 hours and the results showed 77% accuracy [25].

Zhou et. al explore usage of big multimedia data extracted from social media such as Instagram for discovering drug use patterns with respect to demographics. Drug related Instagram posts were mined to find common pattern of drug users in terms of age and gender in respect to time and location of the Instagram post [26]. Taking cues from these work we study the impact of drug related posts by finding the number of tweets with different drug names in cities of Delhi and Bangalore. Then we find whether the tweet has positive or negative sentiment. As negative sentiment tweet will impact society negatively.

Biyani et al. [27] introduced a semisupervised sentiment analysis method that analyzes posts about cancer. The authors used SVM, NB, logistic regression, bagging, and boosting classification algorithms to perform the experiment. Na et al. [28] proposed an aspect-level sentiment analysis method which is applied to drug reviews. They defined a set of rules in order to calculate the polarity value.

Taking cues from these work we study the impact of drug related posts by finding the number of tweets with different drug names in cities of Delhi and Bangalore. Then we find whether the tweet has positive or negative sentiment. As negative sentiment tweet will impact society negatively. For this we develop a computational pipeline for collecting, processing, and analyzing tweets to find signals about adverse drug reactions, defined as drug side effects caused by a drug at a normal dose during normal use.

3. RESEARCH METHOD

The Continuous post of drug associated text in social media, impact the Intoxication society. This scaling arises several problems as the human brain affected by drug does not perfectly fit to perform any task which may lead to unaccepted activities in every task performance such as in driving: accident may happen, in discussion: aggressiveness, in decision taking: not received the desires of perfection, health: degrades the capability.

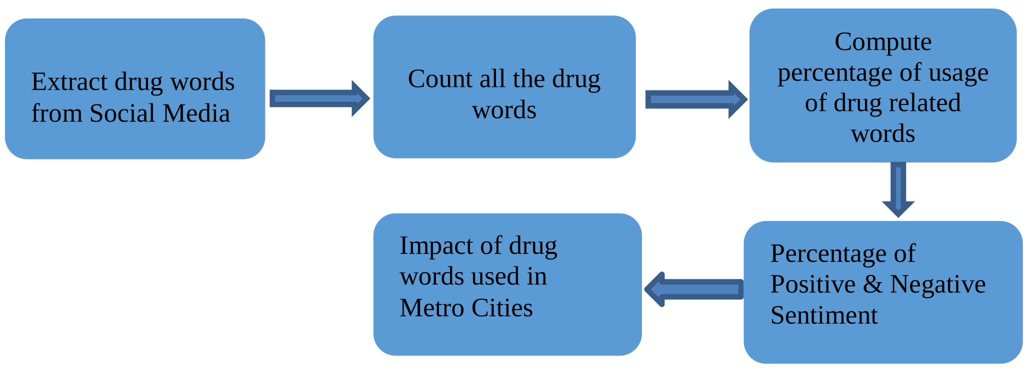

Figure 1. Framework of proposed methodology

Figure 1 depicts the block diagram of proposed methodology to study and analyze the number of tweets in month of November in two metro cities viz. Bangalore and Delhi. The proposed methodology uses common prevailing drugs in society that impact human behavior. Different steps of the proposed methodology are:

a) Extract drug words from Social Media: In this step the names of these drugs are extracted from social media platform like twitter using twitter API. For this we used python library TWEEPY to access tweeter API.
b) Count all the drug words: In the second step all the tweets with the given drug name

occurrence is counted in the given month using respective time and location.

c) Compute percentage of usage of drug: In the third step the percentage of tweets with respective drug names occurring in Delhi and Bangalore are calculated from the total number of tweets. that shows its usage. It also find the metro city that has more contribution related to drug tweets.

d) Percentage of Positive & Negative Sentiment: In this step twitter data containing drug name are analyzed for finding Positive and Negative sentiment analysis. This is done to compute percentage of positive and Negative tweets from the two metro cities for the corresponding drug name. In this step we use TextBlob library of python that is build over NLTK. First the tweets containing drug name is cleaned for stop words and part of speech (POS) tagging is done to extract important words or tokens. These tokens are passed in sentiment classifier that uses sentiment polarity method to get polarity of the tweet between +1 and -1. If polarity is > 0, sentiment of the tweet is positive if polarity is = 0 sentiment is neutral and polarity is < 0 sentiment of the tweet is negative.

e) Impact of drug words used in Metro: This is the last step of our proposed methodology. In this step for each drug, we compute the percentage of positive sentiment and negative sentiment tweets containing the drug name. This will help us find the impact (both positive and negative) of drug words used in the two metro cities.

The first step in the methodology is to shortlist commonly used drugs in society that impact human behavior. We then extract the name of drug words from the tweets in whole month of November. In the second step we count the number of drug words extracted. In the third step we compute the percentage of usage of drug related words and also find the metro city that has more contribution related to drug tweets. We then compare the impact of drug words and analyze it's impact on society.

4. RESULTS

We have computed 21 drug associated words used by people living in prominent cities as Delhi and Bangalore, and found that people do not realize the negative impact of these tweets in society. Table 1 shows the number of tweets in month of November for different drugs in metro cities of Delhi and Bangalore.

We chose Delhi as capital city and Bangalore as IT capital with intellectuals. Table 1 shows city wise contribution of tweets in month of November for different drugs. For Bangalore drug related post contribution is 53.5% and for Delhi it is 46.42. After analyzing these drug related tweets for computing its positive or negative impact on society, we computed the sentiment analysis of these tweets for each city.

Drug name	**Total tweet**	**Bangalore contribution (in %)**	**Delhi contribution (in %)**	%age of tweets showing positive sentiment	%age of tweets showing negative sentiment	%age of tweets showing Neutral sentiment	Positive tweets Bangalore contribution (in %)	Positive tweets Delhi contribution (in %)
Alcohol	49406	41.57	58.43	69.41	21.35	9.24	45.57	55.43
Club	30805	99.83	0.17	56.23	42.45	1.32	95.83	04.17
Cocaine	52655	39.35	60.65	84,45	12.34	3.21	41.34	59.65
Fentanyl	3043	43.81	56.19	54.56	42.73	2.71	43.80	56.19
Hallucinogen	377	13.27	86.73	67.21	23.18	9.61	23.26	76.73
Heroin	8094	38.65	61.35	69.83	25.12	5.05	39.64	60.35
Marijuana	37865	75.98	24.02	68.24	26.35	5.41	71.68	28.32

MDMA	1811	52.62	47.38	56.56	34.34	9.1	55.63	44.37
Methamphetamine	10109	98.58	1.42	65.31	32.21	2.48	98.58	1.41
Opioids	2878	46.17	53.83	56.56	35.18	8.26	42.27	57.73
Steroids	4286	39.11	60.89	52.67	42.12	5.21	31.39	68.61
Tobacco	9802	47.89	52.11	81.58	15.23	3.19	48.79	51.21
Beer	65819	85.28	14.72	52.26	46.67	1.07	85.28	14.71
Wine	23913	59.59	40.41	51.58	43.81	4.61	59.62	40.38
Brandy	24382	20.37	79.63	53.13	43.35	3.52	25.37	74.63
Cognac	3335	34.13	65.87	65.17	23.24	11.59	34.13	65.87
Gin	76480	32.10	67.90	54.89	34.13	10.98	29.09	60.91
Rum	37424	46.03	53.97	51.03	41.41	7.56	46.81	53.19
Vermouth	4414	34.98	65.02	53.02	34.64	12.34	38.97	62.03
Vodka	36390	45.01	54.99	49.37	43.37	7.26	47.01	52.99
Whiskey	29294	53.58	46.42	52.56	43.41.	4.03	57.57	42.43
Average	**Total: 512605**	**53.81**	**46.19**	60.26	33.66	6.08	50.90	49.10

Table 1 shows percentage of Positive, Negative and Neutral sentiment tweets for each drug name. Our proposed methodology computed NEGATIVE impact of drug related post by computing average percentage of tweets showing negative sentiment for all drug name. The average percentage of Negative tweets is 60.26%. Similarly Table 1 shows the average percentage of Positive tweets is 33.66%. The average percentage of Neutral tweets is 6.08%..

Table 1. Drug wise Number of tweets, percentage of Negative, Positive and Neutral sentiment tweets in each metro city

We then find the contribution of metro cities for Negative Sentiment tweets. Table 1 shows the Negative tweets Bangalore contribution of 50.90% and Negative tweets Delhi contribution is 49.10 %. Thus results as depicted in Table 1 shows Bangalore has slightly large Negative sentiment tweets contribution that impact society negatively.

Figure 2 demonstrate the table graphically. Figure 2 shows the percentage of tweets related to different drugs such as alcohol, club cocaine etc. Alcohol tweets percentage in Bangalore is 41.57% whereas in Delhi it is 58% whereas Whiskey in Delhi contributes 53.57% and in Bangalore it is 46.2%. After analyzing these drug related tweets for computing its positive or negative impact on society, we computed the sentiment analysis of these tweets for each city. Table 1 shows percentage of Positive, Negative and Neutral sentiment tweets for each drug name. Our proposed methodology computed NEGATIVE impact of drug related post by computing average percentage of tweets showing negative sentiment for all drug name. The average percentage of Negative tweets is 60.26%. Similarly Table 1 shows the average percentage of Positive tweets is 33.66%. The average percentage of Neutral tweets is 6.08%.

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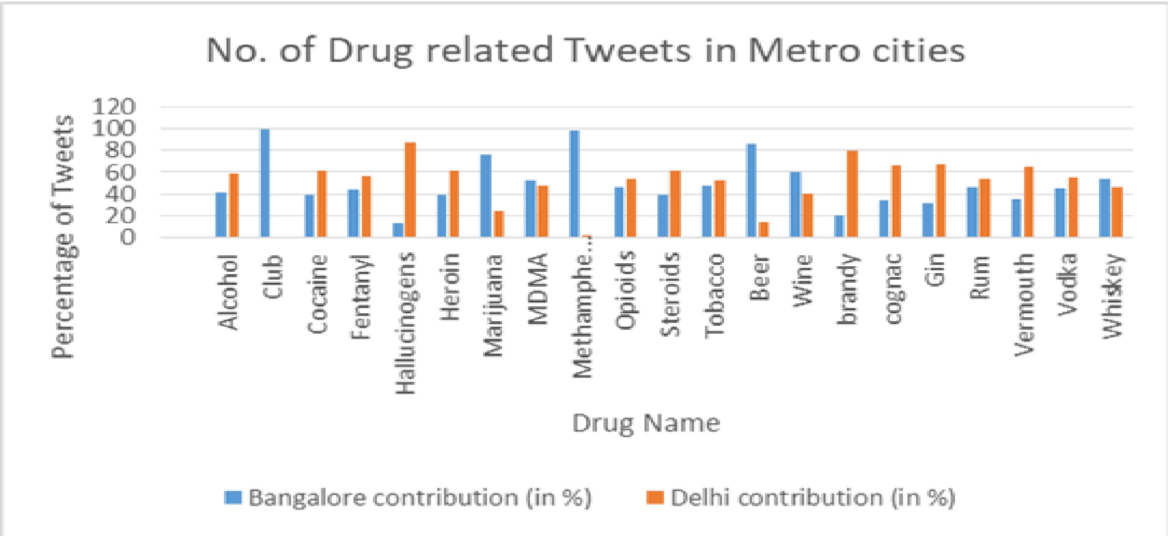

Figure 2. Percentage of Drug tweets in Metro cities

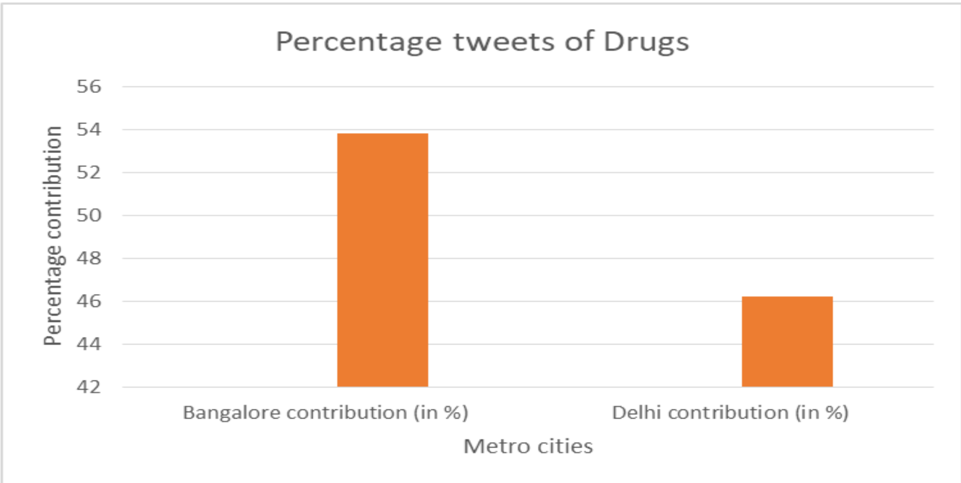

Figure 3. Overall Tweet Percentage of Drugs in metro cities

Figure 4 represents the tweet percentage of commonly used drug such as alcohol, cocaine, heroin, steroids, tobacco beer, wine, brandy, Gin, Rum, vodka and whisky. Figure 5 depicts the percentage of Negative, Positive and neutral sentiment polarity of commonly used drugs. It shows 69.41% of alcohol containing tweets has positive sentiment, 21.45% negative sentiment and 9.24% neutral sentiment.

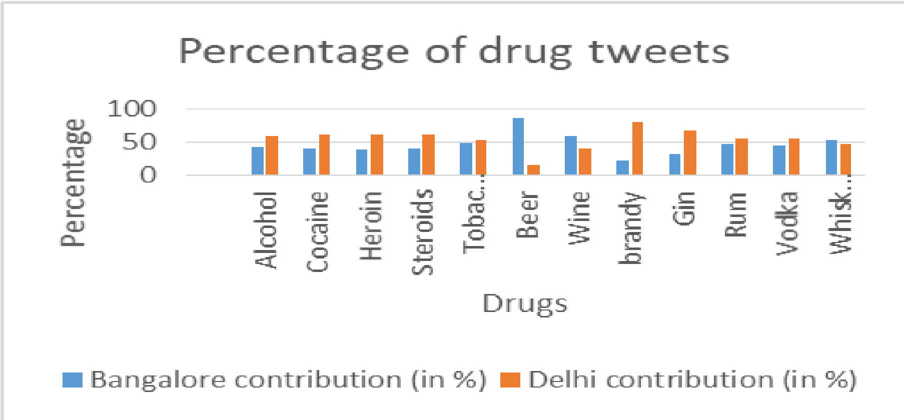

Figure 4. Tweet Percentage of most common used drugs

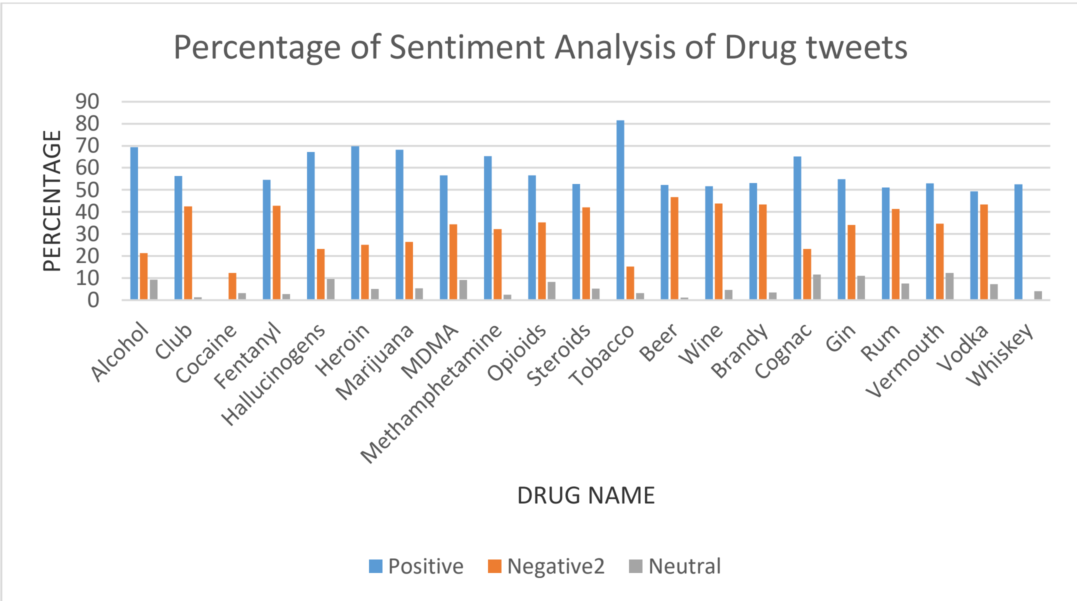

Figure 5. Sentiment analysis of Tweets containing of commonly used drugs

This study concludes that the number of tweets with positive sentiment related to drugs has direct impact on person's mental health. This is because positive sentiments of drugs are related to drug advertisement/drug use encouragement. Whatever a person hears from word of mouth or reads from tweets reflect in their action and impact their health.

5. CONCLUSIONS

Most of the educated people involved in this case live in the capital of India and Electronic (IT Hub) cities, sharing their tweets on social media without thinking about the intoxication impact on society. We identify 21 drug associated words and extract them from twitter in two cities of Delhi and Bangalore in month of July 2019. These words with negative sentiment are directly associated with the society as they impact the health of people. We analyze the sentiment of these drug related posts. The results show that Bangalore contribution in the drug related tweets is more than Delhi that can be accounted as the IT sector people have more physical and mental pressure. So to curb or alleviate the pressure or release their mental tension they get addicted to drugs for enjoyment. In prolong cases, these drug leads to major disease and therefore they need to invest in health related issues which may also reduce their lifespan.

This study analyzes the drug related data in form of tweets from social media where people who are involved are using digital or social media only. In future we plan one to one interaction of people living in these metro cities for primary data collection regarding drug related issue and their investment in healthcare issue, so that more accurate results can be analyzed and will improve their health

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