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Opioid-Related Content on Twitter and the Impact of COVID-19 Government Stimulus Distribution

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OPIOID-RELATED CONTENT ON TWITTER AND THE IMPACT OF COVID-19 GOVERNMENT STIMULUS DISTRIBUTION

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ABSTRACT

The United States has continuously faced an opioid epidemic that has resulted in a severe loss of human life. The coronavirus pandemic began in December 2019 and affected many aspects of daily life. One result of this pandemic was government financial aid in the form of stimulus checks that were directly deposited into peoples' bank accounts. This study aims to understand better the impact stimulus checks had on opioid overdose rates within America by using content collected from Twitter to gauge public opinion. The sample consisted of a stratified random sample of 600 overall tweets that contained at least one relevant search keyword. Keywords were common drug terms. Content analysis was used to determine emerging themes within the tweets to better understand how people discussed opioids. Results showed that there was no discussion by Twitter users that involved stimulus checks in conjunction with opioids.

DEDICATION

This manuscript is dedicated to my father; I hope I have made you proud.

ACKNOWLEDGMENTS

I would like to thank my amazing sisters, Shyla and Sierra. They have constantly supported me in everything that I do, even if it makes me move out of state and far away from them sometimes. I love you both dearly.

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CHAPTER ONE

INTRODUCTION

The use of illicit substances has been an ongoing fight between law enforcement agencies and individuals within the United States. This escalated when President Richard Nixon declared a War on Drugs in the U.S. in the 1970s, making it clear that some substances were illegal to possess and distribute (Global Commission on Drug Policy, 2011). Ever since then, an increasing number of people across the nation have used illicit and addictive substances. This culminated in an opioid epidemic that officially peaked during the 1990s (Center for Disease Control and Prevention, 2022b). As of 2019, 20.8% of people aged 12 years or older used an illicit drug within the past year (Substance Abuse and Mental Health Services Administration, 2020). To put it into perspective, this is roughly 57.2 million individuals. This is an increase from previous years, such as in 2018 when it was 19.4% (Substance Abuse and Mental Health Services Administration, 2019). Although this is not a large difference, this shows that there has been a continuous increase from year to year.

Many scholars believe that the advancement of the internet, such as social media platforms and darknet sites, has enabled the proliferation of drug use and abuse even further (Aldridge & Decary-Hetu, 2014; Thanki & Fredrick, 2016). In this context, social media refers to networking sites that “enable the creation and exchange of user-generated content” (Lai & To, 2015). This includes Facebook, Twitter, Instagram, Snapchat, and Tumblr. Because of the prevalence of various types of crime online (Federal Bureau of Investigations & Internet Crime Compliant Center, 2020), different social media platforms have created community guidelines and terms of service to help prevent and limit the circulation of harmful content. However, these guidelines do not always catch everything posted before users get a chance to see it.

The current literature focuses on myriad different avenues within this overarching topic. Some research addresses how such content will affect adolescents, given their propensity for drug and social media use (Miller et al., 2021). Also significant is the number of articles that have explored the role of social media in predicting and tracking drug use trends or engaging public opinion on the legalization of drugs in general (Yang & Luo, 2017; Motlagh et al., 2019). What the literature fails to do, however, is to assess spikes in drug mentions on social media sites and see if these spikes correlate with drug overdose spikes. Additionally, the connection between drug content and social media is not as well-researched. A vast amount of the literature that addresses drugs online focuses solely on darknet sites such as cryptomarkets (Aldridge & Decary-Hetu, 2014) or on how users purchase drugs within online platforms (Miller & Morris, 2016). This fails to truly showcase how drugs have permeated everyday online interactions, making it easier for anybody to access such substances. Since young adults are the primary demographic using social media consistently (Duggan & Brenner, n.d.), this could lead to many individuals' disastrous short- and long-term health issues.

By researching opioid-related content on social media sites, this exploratory study aims to determine if opioid mentions spike in relation to stimulus check distributions. This is important for future government assistance programs because determining if the form of stimulus checks is increasing opioid use within the United States makes it easy to determine if the way the assistance is distributed needs to be changed in future assistant programs. As part of the Coronavirus Aid, Relief, and Economic Security Act (CARES), stimulus checks were a response to the coronavirus pandemic in the form of Economic Impact Payments to people deemed eligible (United States Government, 2021a). The study will narrow the illicit drug content to specifically be about opioids because of research that showed a spike in opioid-related overdoses during this same time period (Doyle-Burr, 2020; Michael, 2021; Rafferty, 2021). Although all of these sources are news outlets, this highlights how important it is to examine the phenomenon in a more rigorous research aspect thoroughly. The National Survey on Drug Use and Health broke down the category of prescription pain relievers and found that the two most commonly used substances within this category are hydrocodone and oxycodone. Including these two substances, this study will also research fentanyl and heroin. This survey also highlighted the different age groups that most use each of these drugs. For prescription pain relievers, the age group that most often uses them is between 18 and 24 years. This age range corresponds to the individuals who use social media sites. The goal is to better understand the relationship between opioid mentions and stimulus check distribution and social media's impact on drug use.

The following chapters of this proposal will provide the reader with an overview of the literature thus far on illicit drug use behaviors in general, social media use behaviors, how the internet itself has impacted illicit drugs, government financial aid, and the impact COVID-19 had on drug use. Following that is a detailed section on the proposed methods employed within this study. This section highlights the method used for collecting the data and the one utilized for analyzing said content. The current study aims to address the issues laid out above by conducting a content analysis on data gathered with the help of the Social Media Listening Center (SMLC) at Clemson University. By sorting through the posts gathered by the software that the SMLC uses, counting the content to identify any spikes during specific periods of time will be easy to do.

CHAPTER TWO

LITERATURE REVIEW

While there has not been an abundance of previous literature written on the concept of opioid-related posts on social media platforms, there is quite a bit of existing research on illicit drug use behaviors and social media use habits. The review within this proposal begins by delving into the habits and behaviors of individuals who use and abuse illicit drugs. I then analyze how individuals use different social media platforms and the reasons behind certain practices. Furthermore, I want to assess how the internet, in general, has impacted drug use and drug markets. Finally, I will report on the relationship between government assistance and drug use as well as between COVID-19 and drug use.

Illicit Drug Use Effects

When examining what side effects an individual might develop by using illicit substances and what behaviors make a person more likely to use said substances, we must first define what this all refers to. An illicit drug is a substance that can either stimulate or inhibit the central nervous system or cause someone to hallucinate (Uutela, 2001). Examples of stimulants are cocaine and crack or amphetamines. Hallucinogenic illicit substances include ecstasy and LSD (Halpern, 2003). Examples of inhibitors, also known as depressants, are opiates and barbiturates (Cordovilla-Guardia et al., 2019). As evidence, many different substances are classified as illicit, and thus, many different habits a person can develop when using such drugs.

One of the prominent theories behind drug use is the social learning theory. Broadly speaking, this theory states that people can learn new deviant behaviors from observing their peers and imitating them (Piquero, 2016). When applied to drug use, the theory hypothesizes that people are more likely to use illicit substances whenever the people they associate with also use illicit drugs or when such behavior is positively reinforced. Therefore, social media could seriously impact individuals and drug use. When someone sees their online friends posting about using drugs and getting a lot of positive interaction from it, such as many likes and comments, social learning theory says that they have a higher chance of then picking up the behavior themselves. Research has even been conducted to assess how virtual peers impact deviant behavior compared to traditional face-to-face peers (Miller & Morris, 2016; Nodeland & Morris, 2020). This study found that online friends can have just as much impact on a person's behavior as their traditional friends do (Miller & Morris, 2016).

Opioids. Drugs classified as opioids relieve pain by connecting to opioid receptors within the brain and body, suppressing how an individual perceives pain (Krieger, 2018). Opioid use leads to death when taken at higher doses because these drugs cause an individual's heart rate to slow as well as their breathing. This is due to their nature as a depressant or an inhibitor. As of 2019, over 49,860 overdose deaths were related to opioid use (Center for Disease Control and Prevention, 2021). Additionally, opioids can be highly addictive, especially when an individual is taking them to treat chronic pain. This, in part, is due to the body developing a tolerance to the drug

(Benyamin et al., 2008). An individual builds up a tolerance to where a certain amount of the drug will no longer be as adequate as before, forcing them to take higher doses.

Research also suggests that opioids affect hormones as well. Furthermore, specific opioids can have specific side effects. For example, hydrocodone can cause side effects such as dizziness and nausea (Benyamin et al., 2008; Porreca & Ossipov, 2009). Oxycodone can cause constipation, headaches, drowsiness, and many more symptoms (Anastassopoulos et al., 2011). Some common side effects of fentanyl use are vomiting, vertigo, and hallucinations (Han et al., 2019). Heroin is a different type of opioid from the previously mentioned in that doctors do not prescribe this drug, although it had been in the past. It has been noted that people who become addicted to prescription opioids often turn to heroin use whenever they can no longer obtain the prescription drugs (Salani et al., 2016). This is because heroin is easy to obtain on the street while others such as hydrocodone and oxycodone, often require prescriptions. Because of this difference between prescription opioid use and getting substances off the street, there is a distinct difference between recreational versus using prescription drugs as they are intended. Recreational use would be using opioids with the intent to get high (Pino et al., 2017). Opioid misuse is described as “selling and diverting prescription drugs; seeking additional prescriptions from multiple providers; and manipulating the formulations to use them in a manner in which they are not intended (e.g., snorting, injecting)” (Butler et al., 2007, p. 2). Not all of these aspects will be viewable through online social media posts. However, some information will be noticeable enough to determine if someone posts about misusing opioids. This will be discussed more within the methods section, as well as the other codes used within this study.

The Internet and Illicit Drugs

The introduction of the internet had an astounding impact on society. It has led to more people easily and efficiently working, learning, and producing while also allowing individuals to better inform themselves on various topics (Nie & Erbring, 2002). However, this ability to widely spread information and media content as well as connect with anyone anywhere on the planet has had severe consequences, specifically when related to criminal activity. With the ability to make connections with people anywhere in the world in a matter of minutes comes an increased risk for such things as theft, fraud, and abuse. The Federal Bureau of Investigations lists some common cybercrimes such as identity theft, spoofing, and phishing which refers to "schemes aimed at tricking you into providing sensitive information to scammers," and many more (The Cyber Threat, n.d.). One way the internet influences drug use is through the concept of social learning theory. This theory explains that criminal or delinquent behavior is learned by operant conditioning. Operant conditioning is behavior controlled by the consequences the person will receive (Piquero, 2016). In essence, this means that people on social media will imitate the behavior of others, such as posting about drug use, whenever they see one of their friends post about using substances and getting positive attention because of it.

Social Media Use

How people use and interact on social media platforms varies based on factors such as age and personality. One study found that people who use social media often exhibit traits of being conscientious and are open to new experiences (McGahey, 2019). Social media, also deemed social networking sites, are currently defined as online platforms where users can create profiles, make and connect with friends, create and upload videos and other media content, and browse existing content such as ads and current events (Rhee et al., 2021). This is a very open description. While on social media sites, users can post videos or photos, say what is on their mind, view and shop with targeted ads, read news articles and, learn about political events, keep up to date with what is happening in other parts of the world, talk to friends and family, and view trending topics within different categories. A study conducted in 2016 found that among young adults, 97.5 percent of the individuals sampled used at least one platform, and they used such platforms regularly (Villanti et al., 2017). The top five sites used by this demographic were Tumblr, Vine, Snapchat, Instagram, and LinkedIn, with Google+, Facebook, and Twitter being close in number. That being said, Vine is no longer accessible to users, and LinkedIn has a more professional undertone. This list also does not have Instagram as part of it, which is now a major photo networking site.

Opioids on Social Media. Although there have not been an abundant number of studies conducted that address the topic of opioids appearing on social media, this topic has been broached before. One such study conducted in 2015 focused on assessing Twitter data to better understand the public's opinion concerning nonmedical prescription opioid use (Chan et al., 2015). The researchers employed content analysis methods of analyzing their data and found that 70% of their data referenced people using opioids to get high or other misuse behaviors. Another study also published in 2015 found similar results. Researchers assessed tweets concerning prescription opioids and found that over 66% of their data addressed a positive sentiment toward misusing opioids and addiction to such drugs (Shutler et al., 2015). One article focused on the nonmedical use of prescription medicines and online pharmacies that sell illicit substances through Twitter. The researchers found an abundance of tweets that provided direct links to online pharmacies, promoting the illegal sale of prescription medicines (Katsuki et al., 2015). Yet another article published in 2016 determined that through manual analysis of tweets mentioning the abuse of specific medications, Twitter and social media, in general are a good source for gathering data about the abuse and misuse of medications (Sarker et al., 2016). Each of these articles listed above also points out that Twitter, or social media in general, is an excellent tool for gaining insight into public opinion and observing drug trends (Chan et al., 2015; Katsuki et al., 2015; Shutler et al., 2015).

Government Assistance and Drug Use

The aim of assistance programs headed by the United States government is to provide economic security to individuals who qualify (U.S. Social Security Administration, 1944). This assistance can come in many different forms. For example, some of the current financial assistance programs are the Adjustable Rate Mortgage Insurance program which helps with housing, the American Opportunity Tax Credit, which helps with higher education expenses, and the Projects for Assistance in Transition from Homelessness which helps people who are or will be without a home, and many more (United States Government, n.d.). These programs arose from specific needs being addressed within society. Because of this, there are certain times that other, less permanent programs might arise. One of these occurred recently within history. This is the coronavirus pandemic that began in December of 2019. The virus sent shockwaves all over the world. One shockwave within the United States is how the quarantine aspect of the pandemic caused mass unemployment rates. This led to many people no longer being able to afford their current living conditions and lifestyles. Because of this, government assistance programs arose to provide support for people affected by the pandemic. One such program was the distribution of stimulus checks. The United States government distributed up to three checks to people in need to assist with food, housing, and bills (United States Government, 2021b). The first check equaled $1,200, the second was for $600, and the third was for $1,400. These checks were either directly deposited into a person's bank account, or a physical check was mailed to the recipients to be cashed in later.

Unfortunately, with these checks, there was no way to limit what the money was spent on. With assistance like this, where money is being directly given to people, individuals can spend this on whatever they please. This means that, if they so choose, individuals could potentially spend this money on drugs. There has even been research conducted on this that has found that there is, in fact, a correlation between social assistance and drug use (Krebs et al., 2016; Richardson et al., 2021). To combat this, some programs have switched the mode in which money is distributed. One example of this is the food stamp system, where money is put onto electron benefit transfer cards which work at certain stores that sell food. By restricting the way in which financial assistance can be used, this could lead to a decrease in drug use and abuse.

COVID-19 and Drug Use

The COVID-19 pandemic, also known as coronavirus, struck the world in December of 2019 within the Hubei Province in China (Center for Disease Control and Prevention, 2022a). By January 18th, 2020, the United States had its first confirmed case of COVID-19, and by the 31st, it would be declared a public health emergency within the nation. This quickly led to the World Health Organization declaring it a pandemic by early March (Center for Disease Control and Prevention, 2022a). By stating that COVID-19 is a pandemic, the nation was quickly thrust into a vastly different day-to-day life. Within a matter of days, parts of the United States began to shut down. From schools to restaurants, everywhere began to close up shop with a stay-at-home order being mandated across the country. Social distancing measures were also put into effect, as well as facial mask mandates. Because of such a response, the majority of the United States population had to stay inside their homes for an extended period of time. This led to a decrease in face-to-face interactions and an increase in drug use (Mcclain et al., 2021). Consequently, this also led to increased drug overdoses in some areas (Glober et al., 2020). Glober et al. also found that drug-related overdoses continued to increase even after the stay-at-home order was lifted within Indiana. This shows that drug use during the pandemic did not suddenly stop. The pandemic also led many opioid users to stop receiving treatment for their addiction, leading to individuals relapsing into opiate use once again (Sun et al., 2020).

CHAPTER THREE

METHODS

The literature review listed previously summarizes the current and past research on both social media use as well as illicit drugs and how they overlap. Furthermore, it also provides a background on how government financial assistance has impacted drug use in the past and the impact of the coronavirus on the world in general. What each of the previously listed studies fails to assess, however, is the current state of opioid-related content on Twitter and how coronavirus measures might have affected it. Furthermore, the current study differs from that of previous research in the sense that content will be assessed from both prescription and non-prescription opioids. Data were collected on three prescription opioids and one illegal opioid. As stated previously, the general aim of this study is to better understand the relationship between opioid-related content on social media sites and stimulus check distributions. As a result, two questions were fashioned:

1. Were there noticeable spikes in opioid mentions on Twitter relative to stimulus check distributions?
2. What are the emerging themes of posts with opioid-related content?

Because the effect that Covid-19 had on social media and drug use, in general, has yet to be fully researched, my approach was exploratory and did not have a large theoretical basis for building upon it. For this reason, there were not necessarily hypotheses supported by previous research or theories either. However, I hypothesize that there would be an increase in the frequency of mentions of opioid misuse. Specifically, I think the increase will fall within the stimulus distribution dates. I also hypothesize that one prominent theme among the content will be that people will anticipate receiving the stimulus checks and wish to use the money to purchase opioids.

This study (IRB2022-0041) was determined by the Clemson University Institutional Review Board on January 27, 2022, to be exempt under Exemption Category D4 in accordance with federal regulations 45 CFR 46.104(d).

Data Collection

To answer research questions, I conducted various keyword searches on posts found through Clemson University's Social Media Listening Center. The software the center uses to collect the data is called *Sprinklr* and works by typing in keywords and pulling any content from selected sites that contain said keywords (Sprinklr, n.d.). The system then shows many different analytics for the given word, such as how many overall posts and comments contain the keyword(s), the reach of the topic, the net sentiment, and the emoticons that are most used along with the keyword, as well as a demographics section.

The content was narrowed down to only include data from Twitter since this is the social media platform that the software has the ability to pull data from and is also not an image-based platform. Unfortunately, the software used for the study does not have a way to analyze images, so the only way a post that contains an image would be collected via the software is if it had a caption with it as well, and that caption contained the search terms. A future study should employ software that can recognize different aspects of images.

Data was also confined to posts specifically geolocated from the United States. This is because the U.S. is where stimulus checks were distributed. This study is also narrowed down to posts that come from specific dates in time in relation to the dates surrounding check distributions. The first check was distributed to individuals in April of 2020. The second was distributed starting December 29th of 2020 and into January 2021, and the third check was distributed in March 2021 (United States Government, 2021). For this study, data were collected during these months as well as during three random months outside of these dates as a control for comparison purposes. This results in a total of 4 distinct time periods from which data is collected.

Keywords. In order to collect the data, a detailed keyword search was first obtained. The method of finding relevant keywords was simply to pull various lists from peer-reviewed articles as well as do a Google search for common opioid-related hashtags and slang terms. The initial keywords for each opioid are listed in Table 1. These terms all come from many different sources. One such source was the Urban Thesaurus which is a site that is an index for slang terms that are collected from popular sites where people can create and define terms (*Urban Thesaurus - Find Synonyms for Slang Words*, n.d.). Words were also found in a report conducted by the Drug Enforcement Administration, which was published in 2018. The Snohomish Health District has also created a list of slang and keywords for different drugs (Snohomish Health District, 2019). Finally, two published peer-reviewed articles were also consulted when compiling the list of search terms (Cherian et al., 2018; Li et al., 2021).

Table 1: The Initial Keywords for Each Opioid Searched

Hydrocodone	Oxycodone	Fentanyl	Heroin
Hydrocodone	Oxycodone	Fentanyl	Heroin
Vicodin	Oxycontin	Duragesic	H
Lortab	Percocet	Actiq	Smack
Lori	Oxycet	Sublimaze	Dope
Lorcet	Oxycotton	Apache	China White
Vike	Hillbilly Heroin	China Girl	Horse
Vees	Percs	China White	Skag
Watsons	O	Dance Fever	Junk
Vics	Ox	Goodfella	Black Tar
Hydros	Blues	Jackpot	Big H
Scratch	512s	Murder 8	Brown Sugar
Norco	Kickers	Tango and Cash	Mud
Idiot pills	Killers	Tnt	Dragon
Tabs	Oxy	Dragon's Breath	Mexican Brown
357s	Oxyclean	Fenty	Thunder
Dones	Roxy	Fent	Skunk
Droco	Roxi	King Ivory	Big Harry
IP109	Oxynorm	White Girl	Birdie Powder
IP110	A215	Birria	Fairy Dust
Zohydro	K8	Chyna	Chiva
M367	Oxyneo	Acetylfentanyl	Speedball
	M15	Phenaridine	Pearl Tar
	M30		Diacetylmorphine
	A15		Gunpowder
	OC30		
	OC80		
	OP80		
	M523		
	IP204		
	C230		
	V4812		
	CDN80		

The Process. The data collection part of this project was a three-step process. The first step was to input a list of slang terms for one specific opioid (hydrocodone, oxycodone, fentanyl, and heroin) into the search bar and then selecting the filters for location, language, and for the source to be Twitter. Then the correct date range was selected. Once these specifications were made, the Sprinklr software pulled all of the tweets that contained any of the keywords listed within the search bar. From there, the second step began. I looked through the top hashtags used, the top terms used, as well as the top themes used to pick out words and phrases that specifically did not address opioids or the use of opioids in any way. When looking at any word or phrase, I meticulously searched through each conversation stream to fully determine if the word in question addressed opioids in any way. Once determined that a word did not add any pertinent information to the dataset, that word would be excluded or taken out of the search results. The words or phrases that were specified as not being part of the results are marked by NOT, so the software knows not to include them within the results. This process was repeated for every opioid throughout every date range. After each keyword was checked to make sure it returned posts that actually pertained to the topic, all of these keywords were then combined into one overall search for each data range. This was the third and last step. To make sure the data from each date range is comparable, the same exact keywords were used for each final search, with the keywords only being checked for pertinence within the first stimulus check date range. This final selection of keywords that were used is shown in Table 2. Then, a random selection of 10,000 tweets per each date range was exported into an Excel file from which a random selection of 100 tweets per date range was selected for full content analysis. This resulted in a stratified random sample with a total sample of 600 tweets. This sample size was determined based on the time allotted for the project as well as the fact that the past literature proposed wildly varying sample sizes for similar projects. Although this was a lengthy process, valuable and pertinent data was collected as a result.

Table 2: The Final Keywords Used in Search

Heroin	Zohydro	Roxy 30	Oxycodone	M30	Black Tar	Oxycotin
Mexican Brown	Percocet	Roxi	Chiva	Oxycet	Fentanyl	Hydrocodone
Duragesic	Vicodin	Hillbilly Heroin	Actiq	Lortab	Percs	Sublimaze
Ox	China Girl	Vicos	512s	China White	Hydros	Fent
M523	Oxy	NOT "Honeywell"	NOT "fortunate"	NOT "fortnite"	NOT #defstar5	NOT #shopmycloset
NOT "Obama"	NOT "bts"	NOT #help	NOT "bruce wayne carter"	NOT #the1975	NOT "wacko"	NOT @WAQTA
NOT @h_mitchellphoto	NOT "art"	NOT "mike moss"	NOT "changkyun"	NOT #NFLDraft	NOT "thelastdance"	NOT #dnd
NOT "bigredmachine"	NOT "acid"	NOT "window"	NOT "hydroxychloroquine"	NOT "live"	NOT "norco, ca"	NOT bike
Oxynorm	Oxycotton	Lorcet	Norco	NOT "bikes"	NOT "bank robbers"	NOT "in norco"
NOT #djburn	NOT "prize"	NOT "norco, california"	NOT "norco ca"	NOT "bank"	NOT "city of norco"	NOT "riverside"
NOT "norco high school"	NOT @norcohssoftball	NOT "ox year"	NOT "year of the ox"	NOT "ox tail"	NOT @roxi_usa	NOT "jazz"
NOT "commercial"	NOT $oxy	NOT "Khashoggi"	NOT "cats"	NOT "rapists"	NOT "nfl"	NOT "draft"
NOT "pulse ox"	NOT "ox tails"	NOT #bysupply	NOT "beastmorphers"	NOT "stalled ox"	NOT "beast morphers"	NOT "roxy striar"
NOT @mollyy_ox	NOT @OX_VT	NOT @oxy_football	NOT "donkey"	NOT "dog"	NOT @roxystriar	NOT "duel"
NOT "samsung"	NOT "bridge"					

Content Analysis

This study employed content analysis methods of examining the collected raw data to determine emergent themes. This is due to the fact that this is a very exploratory study and lacks a substantial amount of theoretical and empirical knowledge to build off of. That being said, both deductive and inductive analysis were used within this project.

As part of the deductive analysis, themes were gathered from previous empirical research, whereas for inductive analysis, the themes were created by me to determine what new themes emerged outside of the ones previously defined by past research. By analyzing the data first with the codes created from previous articles, I was able to examine the data with solid definitions of categories in mind and then go back a second time and re-analyze the tweets to delve further into the information presented and create new additional themes that fit the data best.

The Coding Process. The coding conducted as part of the content analysis for this project was done manually and based on the techniques laid out in "The Coding Manual for Qualitative Researchers," written by Johnny Saldaña and published in 2016 (Saldaña, 2016). This process began by reading through each of the 600 tweets individually and developing categories that sum up the overall theme of the tweet. The unit of measurement for the current project was individual Twitter posts. Also worth noting, each tweet was treated as an individual piece of data which means that retweets of posts were counted as individual posts. To put it simply, even if a tweet was the exact same words as another one within the dataset, it was still counted as its own individual post. This overall process of coding was completed twice to ensure that the themes developed fully encapsulated the content. Additionally, by using Saldaña's book as a guide, I determined that the best method for this project was that of descriptive coding. This is where themes are created that summarizes the topic of each data point (2016). The categories of themes for the current project began by developing three overall sections: Personal Experience, Public Opinions, and Not Relevant. Each of these sections was further broken down, which is depicted fully in Figure 1. When constructing these categories, inspiration was drawn from previous research, such as the peer-reviewed article that focused on gauging public opinions and behaviors surrounding nonmedical prescription opioid use (Chan et al., 2015). This past empirical study developed codes through both inductive and deductive reasoning based on definitions of prescription drug abuse as well as the Current Opioid Misuse Measure, which is a self-assessment used to monitor patients who suffer from chronic pain taking prescription opioids. The researchers also created the codes based on pre-existing studies (Chan et al., 2015). Because this study additionally focuses on the different health attitudes surrounding opioids, not all of the codes and definitions used within their content analysis coding were employed within this current study. However, the themes that were taken from this article are indicated in tables 4 and 5. The current study then produced codes through an inductive analysis approach where themes came about as the data was analyzed. For example, because one major concern within the general public right now is the legalization of marijuana, one theme that was made specifically for this study is tweets that pertain to comparing marijuana to opioids. The data gathered for this project was then manually coded within Microsoft Excel, and frequencies were conducted by hand. The results gathered are explained down below.

Figure 1.1: Chart of Categories of Themes Constructed During the Coding Process

Personal Experiences of Behaviors Concerning Opioid Use	**Public Opninion**	**Not Relevant**

• General Misuse Behaviors
• Side Effects of Misuse
• Addiction or Overdose References/Stories
• Recovery Stories/Staying Sober
• Side Effects of Use (ambiguous)
	• Public Health Awareness
	• Marijuana Legalization
	• Pop Culture References
	• Negative Sentiment Towards Opioids
	• Positive Sentiment Towards Opioids
	• Comments on Someone Else's Use
	• Used in Medical Settings
	• Addressing Politics or Political Figures
	    • Addressing China and Their Influence
	• Addressing Police or Government Efforts
	• Used as an Insult
	• Addressing Covid-19
	• Other
	    • Unclear Mentions of Opioids
	    • Mentioning Opioids as a Simile or Metaphor
		• Referred to Non-Relevant Use of Search Terms
		• Originated from Users' Profile Names
		
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CHAPTER FOUR

RESULTS AND DISCUSSION

Research Question One

The first question this study aimed to answer was, “Were there noticeable spikes in opioid mentions on Twitter relative to stimulus check distributions?” The data collected for this question is presented in Table 3. Within this table, it is clearly visible that the control groups for rounds 1 and 2 garnered more Twitter posts that contained the listed keywords when compared to their corresponding stimulus check groups. However, for round 3, the stimulus check group actually contained 57,290 more posts when compared to the control group. This increase from the round three control group to the stimulus group is increasingly interesting since the initial stay-at-home orders were issued around March 1-May 31st of, 2020. Because more people were now ordered to stay inside, it would stand to reason that more people were spending their abundant free time browsing social media sites. However, the results do not support this since round 3 fell outside of this stay-at-home date range. These results also do not fully support the hypothesis originally presented. Although there was an increase in opioid mentions over time, only the last round showed an increase during the stimulus check date range.

Table 3: Number of Mentions Per Date Range

	Control 1: March 23-April 23, 2020	**Stimulus Round 1:** April 24-May 24, 2020	**Control 2:** Nov. 29-Dec. 29, 2020	**Stimulus Round 2:** Dec. 30-Jan. 30, 2021	**Control 3:** Feb. 12-March 12, 2021	**Stimulus Round 3:** March 13-April 13, 2021
Final Number of Mentions	76.87K	71.94K	113.87K	77.28K	104.06K	161.35K

Research Question Two

The second question this study aimed to answer was "What are the emerging themes of tweets that contain opioid-related content?" To find answers to this question, a content analysis of every tweet within the sample was conducted. After the analysis was finished, frequencies were calculated. Overall, this project analyzed a total of 600 Twitter posts. A total of 126 (21%) were excluded because they did not pertain to the topic of opioids but were collected in the overall sample because the keywords used could refer to things outside of opioids. Even though steps were taken to help cut down on the amount of extraneous tweets collected, it was impossible to completely narrow down the search results to only contain tweets that addressed opioids since the software only allowed 100 terms to be input into the search bar. Results show that the group that had the highest number of tweets that fell under the general category of personal experience was the first control group, with roughly 13% of the tweets within that group falling among this category. This is interesting considering the control group occurred from March 23-April 23, 2020, and was before any of the stimulus checks were distributed. This shows that the group that contained the lowest number of tweets within this overall category was a tie between control group 2 and stimulus round 3 at just 6% of their entire group makeup. Additionally, the hypothesis for research question two could not be accepted either since there were no tweets that discussed stimulus checks, let alone in correlation to spending them on opioids.

Personal Experiences of Behaviors Concerning Opioid Use. Of the total 474 relevant tweets, 10% (46 tweets in total) contained themes of personal experiences with opioid use behaviors (Table 4). Further, among the 46 tweets within this category of personal experiences, 41% were tweets that addressed the Twitter user expressing behaviors of opioid misuse. Overall, the results show that the majority of tweets gathered did not mention personally using these specific opioids in negative ways. When beginning this project, I expected to find themes expressing wanting to buy or sell opioids. However, when looking through the tweets among the sample, only one tweet addressed having opioids for sale, and this was for Percocet. For this reason, this tweet was categorized under the theme of general misuse and did not warrant a separate category of its own. The vast majority of the tweets collected fell among the subcategories within the public opinion classification.

Table 4: Breakdown of themes among the overall category of Personal Experiences of Behaviors Concerning Opioid Use, with example tweets and frequencies. (n=46)

Themes:	**Example Tweets:**	**Frequencies (%):**
General Misuse Behaviors`	Tara and I have gone from “let’s dye our hair purple” to “let’s do Oxy” in the matter of an hour, send help.. (send Oxy wink wink)	19 (41%)
Side Effects of Misuse	Some drugs make you fat. My husband use to have a problem with norco and those things made him pack on the pounds lol	4 (9%)
Addiction or Overdose References/Stories	In all honestly, yesterday was the shittiest 4/20 to try to celebrate because it had been exactly a year & a half since my only brother overdosed by fentanyl poisoning. My mother & I went to the park and saw his memorial bench in person for the first time since it was put up. 🌹	5 (11%)
Recovery Stories/Staying Sober	A year ago today was the day I stopped using heroin. Two weeks from now I'm	12 (26%)

	moving in with one of my best friends in a new city, starting a new journey. It gets better, y'all, it really does.	
Side Effects of Usage (Ambiguous)	I took an oxy and me sleepy 😔	6 (13%)

`Coding themes based on a prior study on nonmedical use of opioids

Public Opinion of Opioids. The vast majority of the tweets sampled portrayed themes falling under the overall category of public opinion, which showcases the general perceptions that individuals have about opioids (Table 5). Of the total 474 tweets that pertained to the overall topic, 90% (428 tweets in total) contained themes that fell under this umbrella of topics. Additionally, among the 428 tweets, 21% of them were sorted into the theme of addressing politics or political figures. Also, 12% of the 428 were sorted into the theme of comparing opioids to marijuana with the intent of expressing support for the legalization of marijuana. This specific theme was not one that I initially expected when beginning this project. I also did not expect to find tweets that mentioned opioid use as a way of insulting someone. With these tweets, it was evident that opioid use was seen as a negative sentiment. However, it is a very destructive manner. Another theme that arose while analyzing the data was that of opioids being mentioned as a simile or comparison of something else. An example of this would be a tweet that stated, "If you drink whipped coffee it feels like shooting heroin."

Table 5: Breakdown of themes among the overall category of Public Opinion of Opioids in General, with example tweets and frequencies. (n=428)

Themes:	**Example Tweets:**	**Frequencies: (%)**
Public Health Awareness`	A year ago I spoke at the RX Drug Abuse & Heroin Summit as part of my initiative, #BeBest. Even in these difficult times, please remember to check on loved ones who are struggling	28 (7%)

	with addiction.	
Marijuana Legalization	Marijuana needs to be treated more like wine and less like heroin	50 (12%)
Pop Culture References	my boy jughead off da percs🤣🤣🤣#Riverdale	35 (8%)
Negative Sentiment Towards Opioid Use`	How does one think heroin is okay?How does it look tempting to even try? How does a needle in your arm sound fun? I need these answers, I mean.. I can just ask my baby daddy since he is the expert🤷‍♀️ like I am disgusted with myself daily knowing I have a child by him🤮	37 (9%)
Positive Sentiment Towards Opioid Use`	I woke up to a very sincere message from someone that said "I think Heroin makes me a better person". I think providers are quick to dismiss these feelings because it makes them personally uncomfortable. I know I certainly felt that way at one point in my life.	13 (3%)
Addressing Someone Else's Use`	Heroin is not one of those casual drugs bro. You have a problem.	18 (4%)
Use in a Medical Setting `	I've just been taking OTC Tylonel since I got out of the hospital. Even in the hospital, I stopped the oxy a few days before I got out.	13 (3%)
Used as an Insult	bitches be on percs acting like they're the catch	40 (9%)
Addressing Politics or Political Figures	Biden DOJ nominee Gupta owns millions in stock of company accused of fueling Mexican cartels' heroin production	89 (21%)
- Addressing China and their Influence	Now do the death count for those who died yesterday from the deadly Fentanyl that China is attacking us with	11 (3%)
Addressing Police and	The driver of a GMC Yukon was pulled over for speeding, but when K9 officers	36 (8%)

Government Efforts	got near the SUV, they found what they believe to be 30,000 pills of fentanyl inside the truck.	
Addressing Covid-19	The cure for covid-19 is clearly heroin and meth. Don't believe me show me an addict that contracted The rona this whole pandemic? Don't worry I'll wait.	18 (4%)
Other		
- Unclear Mention of Opioids	Bottle of percs	30(7%)
- Mentioning Opioids as a Simile	I was just thinking. Giving up all that stuff at once is kind of like heroin withdrawal 😊	10(2%)

` Coding themes based on prior study of nonmedical use of opioids

Discussion

The aim of this study was to determine the effect that the stimulus check distributions had on opioid use within America by analyzing Twitter posts. However, it seems that from the data sampled; there were no mentions of stimulus checks in correlation to the three opioids and one opiate that was part of this study. This would lead to the conclusion that, within the context of this project, stimulus checks had no discernable impact on opioid and opiate use.

However, that does not explain the rise in overdose rates reported. Admittedly, this rise could be due to a number of factors. Stay-at-home orders were implemented across the nation within all states. Furthermore, all travel to other countries was heavily restricted as well. An article also suggests that because of the increased difficulty in getting shipments of ingredients or chemicals from other countries to make substances, dealers might turn to cutting their limited supply with other, more hazardous ingredients in order to make their supply last longer (Pardo, 2021). This could be a reason why there was an increase in overdose rates during the pandemic but not a noticeable increase in the discussion of using and abusing such substances online.

An additional reason for this rise could also be that the pandemic made it harder for people with opioid use issues to seek proper and reliable treatment (Linas et al., 2021). One part of this reason could be that the stay-at-home orders made anyone who needed treatment too scared or worried to leave their homes, knowing that they could be putting themselves at further risk by exposing themselves to infection.

Furthermore, this supplements information gleaned from many of the tweets among the sample used within the current study. For example, many tweets addressed how the pandemic was reducing travel and product shipments that were originating from China, specifically in reference to illegal fentanyl. This coincides with the explanation above that focuses on shipments of ingredients being disrupted during the pandemic.

Although the results stated above show no support for stimulus checks enabling opioid use, there are still important implications for both research and policies and practices. This study highlights the different public opinions surrounding opioids and their use which can be built upon to develop better educational tools on the topic of opioid use. Although the use of opioids should never be taken lightly, judging by the vastly negative sentiment surrounding it, it seems most people view others who do use opioids in a negative way as well. This seems to support previous research that was conducted on how others view people who use opioids (Palamar et al., 2011). By combining the categories of “negative sentiment” and “used as an insult” results in at least 18% of 428 tweets that reflect a negative sentiment towards opioid use. This could be very damaging for individuals who genuinely need the drugs to help manage pain and who go through the proper procedures to procure such substances. Individuals who hold such people in negative regard can bully or belittle people simply for trying to help treat their chronic pain. This could lead to individuals no longer using opioids even in their proper way or can lead to individuals no longer seeking treatment for opioid misuse because they are afraid of being stigmatized or belittled. One key aspect of social learning theory is the interpretations or definitions of what is acceptable behavior and what is not, which are bolstered through differential association. This means that by individuals spreading such a strong negative sentiment towards opioid use, this point of view could spread through social learning theory. People learn through others that opioids should not be used, even in their proper ways or that using such substances is frowned upon, so they do not want to risk people finding out they use opioids by seeking the treatment they might need. So, by finding out exactly how people perceive the use of opioids, new ways of educating individuals could potentially reverse the apparent stigma surrounding the issue.

CHAPTER FIVE

LIMITATIONS AND FUTURE RESEARCH

When looking over this project, it is important to remember that this is an exploratory study that employs relatively new methods when looking at social media data and the impact that different aspects of the Coronavirus pandemic have had on society. That being said, this research is still highly valuable. One such aspect is how the method of collecting the data can be used in future research. By using marketing software such as *Sprinklr*, it was easy to determine which slang terms for different drugs were still being used by the public today and which ones were no longer being used to refer to illicit substances. For example, the list of slang terms and codewords for drugs that was released in 2018 by the Drug Enforcement Administration (DEA) listed such words as "big harry," "birdie powder," and "skag." However, when entered into the search bar within the first stimulus date range, each of these slang terms resulted in no relevant tweets. Future research should delve deeper into this phenomenon to better determine which slang terms and codewords are still currently being used by people. This could be vastly beneficial in studies such as this one that rely on trending keywords, especially since the official list from the DEA does not differentiate between which codenames and slang terms are from older time periods.

One limitation of this study resides within the software itself. Sprinklr presented a limitation in the sense that each search had to be limited to 100 terms. This means that the program itself would not allow the results of the searches to be narrowed down to completely eradicate all irrelevant data and only leave behind pertinent content. Although the current project was able to gather 79% of the total data sampled and have it pertain to the topic at hand, studies in the future should strive to either find more specific keywords or other programs that have no restrictions on the searches to help increase this percentage and lower the amount of extraneous data collected. Furthermore, the software failed to establish how many tweets were searched in total, so there is no way of knowing the total amount of tweets that the amounts for the first question are out of. This limits the ability to visualize and see the true comparison of just how many tweets mentioned opioids during certain time frames.

Future studies should also consider assessing additional or other opioids. Although this study researches both prescription opioids and street opiates, it is limited in how many it assesses. By adding more, future research has the chance to compile more robust results and potentially find other opioids that are coming into trend. Also, within the context of the coronavirus pandemic, it would be interesting to see the differences between individuals who began misusing opioids during the pandemic versus those that simply continued the behavior from before the pandemic. Within that same vein, in the future, researchers should look at how discussions on opioids and the use of opioids change over time. The current study focused on analyzing the data as a whole instead of how these conversations evolved over the course of the date ranges. By doing this, researchers could discover new themes and ways in which opioids were discussed as well as potentially notice a difference in themes based on if they are new or recurring users.

Lastly, future studies should also open up this topic to be viewed in the context of different social media platforms. Using an image-based platform might garner vastly different results from the ones laid out here. However, based on how the Sprinklr software works, analyzing images for the current study was not possible. Furthermore, using Reddit could provide an insight into how more community-based social media platforms impacted what was discussed and to what detail. By looking at this topic through the different lenses of different social media platforms, a more holistic view of the effects that stimulus checks had on opioid use and misuse can be gathered.

CHAPTER SIX

CONCLUSION

The current study implemented qualitative research methods to ultimately determine what role the stimulus check distribution program had on opioid use in the United States. This was done through the lens of two distinct research questions. Firstly, were there noticeable spikes in the number of opioid mentions during the times that stimulus checks were distributed? Secondly, in what contexts were opioids being mentioned on Twitter? Although using social media data to discern public opinion on drugs is not a new trend in research, looking at this topic in the context of the recent global pandemic is. Furthermore, the idea of using big data and content analysis to study the same set of questions is also an exploratory and new concept. For this project, assessing big data was used to set a baseline for how many tweets mentioned opioids, and then content analysis was used to determine if these tweets also mentioned stimulus checks and in what context opioids were being discussed. The results of this study ultimately determined that there were no noticeable spikes in the number of opioid mentions on Twitter that were determined to be caused by stimulus check distribution. However, there does seem to be an increase in overall tweets from the first round of control and stimulus check dates to the final rounds. This could simply be due to the increase in internet traffic that occurred from the continuing stay-at-home orders that state governments enacted during the coronavirus pandemic.

In the past, the United States government has found ways of distributing financial aid that limit what the aid can be spent on. A prime example of this is the food stamp system. This allows people to still receive the provided aid and use it for its intended purpose while limiting how easy it is to spend it on other such things as drugs. While the current study did not show that this type of change was necessary, this type of aid should be considered for future policies and programs in order to provide the best benefits possible. This study did, however, determine existing gaps for future research, such as ways to determine what drug slang terms are still being used by the public today, as well as established the overall outlook that individuals have towards people who use opioids. This alone could provide a plethora of valuable information in the realm of drug use, especially as it pertains to such substances being mentioned on social media sites. By taking these suggestions into consideration during future studies and policy implementation, will, hopefully, lead to better public opinion regarding people who rely on such substances to go about their daily lives, as well as better track trending drug slang terms.

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