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The opioid epidemic through the lens of social media: mining digital traces for public health, pharmacovigilance, and rehabilitation.

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Declaration of Authorship

I, Duilio BALSAMO, declare that this thesis titled, "The opioid epidemic through the lens of social media: mining digital traces for public health, pharmacovigilance, and rehabilitation." and the work presented in it are my own. I confirm that:

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- I have acknowledged all main sources of help.
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Abstract

Ph.D. Program in Modeling and Data Science
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Supervisor: Prof. Rossano SCHIFANELLA   Co-supervisor: Dr. Paolo BAJARDI

The opioid epidemic through the lens of social media: mining digital traces for public health, pharmacovigilance, and rehabilitation.

by Duilio BALSAMO

In the last two decades, the United States witnessed a severe public health crisis known as the opioid epidemic, consisting of several staggering waves of drug overdose deaths related to opioid consumption. The surge of addiction to opioids started with a widespread consumption of prescription opioid painkillers and later illegal opioids like heroin and fentanyl, causing an estimated total of half a million deaths. Among the challenges posed by what is currently one of the biggest social and health threats in the United States, we focus on public health monitoring, pharmacovigilance, and aid to rehabilitation. A first challenge is effectively monitoring where non-medical opioid consumption takes place and estimating the extent of drug usage in order to be able to prioritize interventions to avoid overdose deaths. A second one, oriented to pharmacovigilance, is understanding how these drugs, which are often prescriptions intended for therapeutic use, are actually tampered with and consumed for unintended non-medical purposes. A third challenge is understanding how to help those who suffer from Opioid Use Disorder begin and sustain recovery from drug use. In this work, we address these challenges by leveraging digital traces gathered on Reddit. By developing and applying state-of-the-art information retrieval, Machine Learning, and Natural Language Processing techniques to treat the large quantity of data available on this social media platform, we provide quantitative results that offer a novel and data-driven perspective on the subject. In particular, we identify a large cohort of Reddit users exhibiting explicit interest in opioid consumption, and estimate the geographical distribution of the phenomenon at the US state level, showing how Reddit may constitute a valuable resource for public health monitoring. Then, we leverage the content shared on the platform to gain relevant pharmacological insights on non-medical opioid use. We study the temporal unfolding of the adoption of opioid substances and bring evidence of complex patterns of non-medical consumption that include how the drugs are tampered with and administered. We conclude by studying the social dynamics among users who begin opioid use recovery and by investigating the harm reduction potential of Reddit as an online peer support group. The results indicate that a particular recovery-oriented community on Reddit exhibits many characteristics similar to in-person peer support groups by offering peer support, acknowledgment, and encouragement, fostering recovering users to change personal behavior and social group. With this dissertation, we show that thanks to innovative techniques and novel data sources, it is possible to provide a new perspective on pressing and multi-faceted issues like the opioid epidemic, with the hope of possibly informing and helping public health stakeholders.

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Contents

Chapter 1

Introduction

1.1 The opioid crisis

In the last two decades, an overwhelming number of deaths due to overdoses of opioid drugs stroke the United States (CDC. Centers for Disease Control and Prevention, 2019). A staggering amount of nearly half a million people died from an overdose involving prescription opioids, like common painkillers used to treat moderate-to-severe pain and illicit opiates like heroin, and the number of overdose deaths involving any drug quadrupled from 1999. In 2019, of the 193 people who died every day of a drug overdose on average across the US, 136 death per day were associated with opioids, for a total of over 50 thousand yearly deaths (National Center for Health Statistics, 2020). For its rapid diffusion on so many parts of the American society and its devastating social and public health impact, this phenomenon has taken the name of the *opioid epidemic* or *opioid crisis*. The estimated cost of this crisis (in 2016) amounted to 78.5 billion dollars per year (Florence et al., 2016).

The crisis emerged from the interplay of several determinants and evolved in three major phases (Ciccarone, 2019) involving different kinds of opioids and prescription/abuse patterns. The abuse of drug prescriptions became very common in the late ’80s (Leung et al., 2017), evolving into an epidemic in the late ’90s with the widespread consumption of prescription semi-synthetic opioids. Before that period, due to their potency and very high risk of addiction, prescription opioids were only administered by physicians in controlled environments, often in hospitals, to manage the pain of patients suffering from severe conditions and chronic pain.

The reason for the widespread abuse of opioids lies in their capability of chemically inducing physical comfort and powerful feelings of pleasure. These substances act on the opioid receptors in the human brain, releasing signals that sedate one’s perception, slowing the breathing and heart rate, triggering a diffused analgesic effect that easily induces mental dependence. However, the human body quickly develops tolerance to opioids. Hence, progressively higher doses are required to achieve the same analgesic effects, creating physical dependence and potentially causing respiratory failure that may lead to death.

Starting from the late ’90s some pharmaceutical companies introduced in the market novel semi-synthetic opioid pain relievers to treat moderate-to-severe pain, like *oxycodone*, commonly sold under the trade names *OxyContin* and *Percocet*, and *hydrocodone*, available under the *Vicodin*, *Norco* names. During those years, these pharmaceutical companies put a great effort in reassuring the Food and Drug Administration (FDA), the healthcare providers, and the general practitioners of the low risk of addiction associated with this new kind of prescription drugs, also convincing the entire medical community of the urgency to treat patients with moderate pain (Van Zee, 2009). Hence, thanks to their high efficacy as pain suppressants, and supposed low risk of addiction, these painkillers became widely adopted

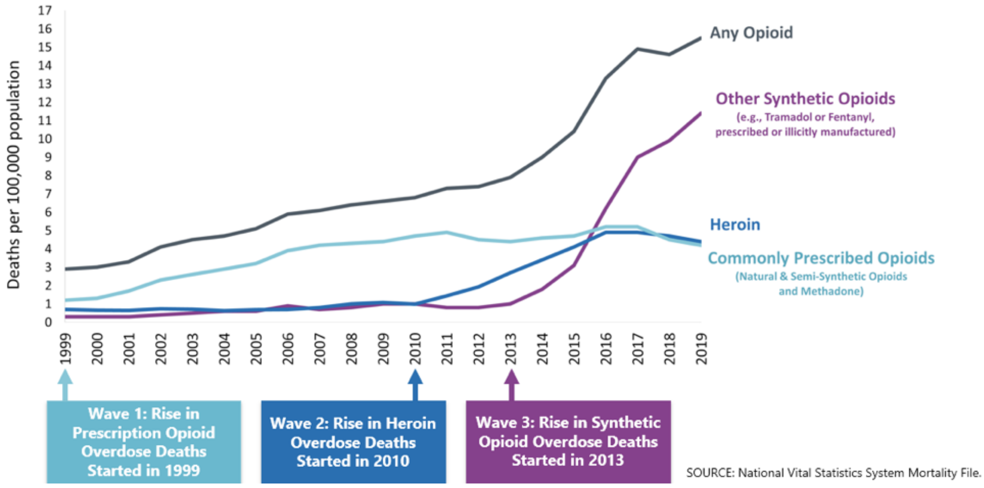


FIGURE 1.1: Deaths per 100,000 US population due to overdose of opioids in 20 years from 1999 to 2019, showing the three waves of the opioid epidemic. Lines of different colors represent the overdose deaths relative to specific opioids.

by the medical community. As a result, in the course of ten years from 1991, the yearly prescriptions of painkillers tripled in the United States (US Surgeon General, 2016). Before it became clear that these medications could indeed be highly addictive, the high prescription rate of opioid painkillers led to a rapid and widespread misuse of prescription and non-prescription opioids, especially in the country's rural areas. Many Americans developed an addiction to opioids, and their increasing need for opioids evolved in a surge of abuse of illicit opioids like heroin (Kolodny et al., 2015; Compton, Jones, and Baldwin, 2016), and the subsequent wave of heroin-related overdoses starting from 2010 (Michel and Loscalzo, 2015). Later, from 2013, the American market was flooded with powerful non-prescription synthetic opioids like *fentanyl* and *tramadol* (Rose, 2017; Ciccarone, 2019), which triggered a new wave of opioid overdoses and deaths.

All these substances, and some new ones, are currently contributing to the growth in morbidity and mortality associated with opioids (Pergolizzi Jr et al., 2018). Today, the problem of opioid misuse is still a significant threat and a pressing social emergency in the United States. A recent study by the Substance Abuse and Mental Health Services Administration (SAMHSA) (2021) estimated that in 2020 a significant part of the population of the United States was suffering from Opioid Use Disorder (OUD), a sub-specific category of Substance Use Disorder. The estimate corresponds to 2.7 million people or 1% of the population of the US aged 12 or older. Very recently, the already fragile physical and mental health condition of those afflicted by the opioid epidemic encountered additional social and health issues triggered by the Sars-Cov-2 pandemic, such as a higher risk of adverse consequences of Covid-19 (Volkow, 2020), leading to a further increase in opioid overdose deaths (The New York Times, 2021).

Even though the United States consume approximately 80% of all the opioids manufactured worldwide, the American opioid crisis potentially threatens the whole world. Prescriptions of opioids and opioid overdose deaths increased in recent years all over the world are not negligible in some European Countries (Schifanella et al., 2020; Hurtado et al., 2020). Luckily, Europe as a whole is not currently facing an opioid crisis of comparable size to the one in the US (Verhamme and Bohnen, 2019;

Häuser et al., 2021). Nevertheless, the renewed availability of heroin and illicit synthetic opioids driven by the high demand in the American market, in combination with the economic recession caused by the Covid-19 pandemic, is potentially leading to a resurgence in nonmedical opioid use in European countries (Seyler et al., 2021; Di Gaudio, Mortali, and Tini, 2021).

1.2 Areas of intervention: from public health monitoring to rehabilitation

Public health authorities and the medical community constantly face the challenges of understanding and limiting the complex social and health consequences of the opioid epidemic. Awareness and abuse prevention campaigns are at the center of the effort, informing, for instance, on the severe consequences of opioid misuse, on how to avoid addiction, how to spot the signs of dependence from drug use in relatives and friends, and how to reverse drug overdoses with naloxone to prevent death. Unfortunately, the list of possible challenges, research fields, and potential areas of intervention span multiple disciplines and can not be addressed as a whole. Hence, in this work we focus on addressing three crucial aspects of the opioid crisis, *public health monitoring*, *pharmacovigilance*, and aid to *rehabilitation*. We believe that targeting these three orthogonal topics may result in a comprehensive understanding of this complex phenomenon, allowing the reader to appreciate three different but complementary aspects, 1) the gravity and diffusion of the crisis, 2) the complexity of drug consumption and administration, and 3) the impact of personal and collective behavior on rehabilitation.

Public Health Monitoring

Governmental organisms like the Centers for Disease Control and Prevention (CDC) displace great resources to monitor where opioid consumption-related phenomena occur. This organization receives and processes the data about prescription opioids, nonmedical opioid uptake, and drug overdoses from the respective health and law enforcement authorities of each US State, with the scope of providing comprehensive and coherent monitoring for the whole country. Estimating the extent and evolution of drug prescriptions and monitoring the usage and adverse consequences of opioids in a geospatial and temporal fashion is paramount to prioritizing the prevention strategies. These interventions might include the development of awareness campaigns, the distribution of opioid antagonists like *naloxone* that reverses an opioid overdose, and coordinating interventions to block the outbreak of potential new waves. Unfortunately, despite the monitoring effort of national and local agencies, the phenomenon of drug usage is intrinsically complex, especially when considering nonmedical behavior, and can be heavily dependent on local conditions. The rate of overdose deaths involving opioids shows, for instance, very heterogeneous geographical patterns in the US, ranging from 4.9 per 100,000 inhabitants in Texas to 43.4 in West Virginia in 2016 (Seth et al., 2018). Moreover, state-level estimates suffer biases due to unequal coverage of the surveillance system, intrinsic biases in counting overdose deaths that lead to low specificity of drugs involved (Hedegaard et al., 2014; Ruhm, 2017; Landen et al., 2003), as well as different prescribing policies implemented by individual States. Besides, due to its reliance on data gathered from different States, the type of monitoring that can be achieved by organisms like the CDC is not timely: drug overdose maps and opioid prescription maps, for instance, are provided only on a yearly basis by the CDC, making the estimations of change rates not particularly effective for prompt intervention. In this perspective, the gold standard represented by official surveillance statistics has to be carefully considered in light of the known biases of the reported numbers and estimates.

Pharmacovigilance

A second aspect to consider when dealing with the opioid epidemic, and which we address in this work, is *pharmacovigilance*, i.e., the science of the detection, assessment, understanding, and prevention of the potential adverse effects of pharmaceutical products. In the US, any activity relating to pharmaceuticals is deputed to one central agency, the Food and Drug Administration (FDA), which monitors the life of any medicine from the authorization to the monitoring of patient safety once the product has received approval. In the context of the opioid epidemic, the primary focus of pharmacovigilance research is to understand the potential misuse of prescription opioids (McCabe et al., 2007; Katz et al., 2008; Butler et al., 2008; Butler et al., 2011; Agnich et al., 2013; Amsterdam and Brink, 2015; Curtis et al., 2019; Richards et al., 2020; Schifanella et al., 2020). Drug manufacturers and the public health administration know and study the adverse consequences of medicine uptake in settings of intended therapeutic use, performed with clinical trials in which patient exposure is limited and closely monitored. However, these settings do no longer hold when considering nonmedical drug consumption. In these cases, the health-adverse risks of the same substances may significantly vary from the expected, potentially causing dangerous health outcomes (Strang et al., 1998; Young, Havens, and Leukefeld, 2010; Butler et al., 2011) Hence, a crucial aspect of pharmacovigilance is monitoring and understanding patterns of drug consumption. This primarily includes monitoring of the various routes of administration (ROA), that is, the paths by which a substance is taken into the body (McCabe et al., 2007; Kirsh, Peppin, and Coleman, 2012; Gasior, Bond, and Malamut, 2016) used for nonmedical consumption. Moreover, many studies (Katz et al., 2011; Kirsh, Peppin, and Coleman, 2012; Gasior, Bond, and Malamut, 2016) acknowledge that drug tampering, that is, the intentional chemical or physical alteration of medications (Mastropietro and Omidian, 2014), is an essential constituent of drug abuse. The alteration of the pharmacokinetics of the opioids through drug-tampering methods, together with the unconventional way in which they might be administered, may potentially lead to very different addictive patterns and ultimately have unexpected health-associated risks (Strang et al., 1998; Kolchinsky et al., 2015). For this reason, effective pharmacovigilance is also fundamental to the research focused on developing tamper-resistant and abuse-deterrent drug formulations.

An additional challenge in the case of opioids lies in the widespread production and consumption of illicit opiates and synthetic opioids. Being illegally refined or synthesized, substances like heroin and fentanyl pose an even more significant threat to public health because such substances are beyond the reach of the quality checks of the FDA and because their diffusion, purity, and dosage are not controlled. Despite the large number of studies dedicated to pharmacovigilance, often performed by means of interviews to opioid users, due to the evolving nature of opioid consumption –driven by the market, by the availability of the substances, and by the habits of those who consume drugs– this matter is still open. Hence, many of its aspects are yet to be explored. In particular, we acknowledge that pharmacological research struggles in spotting unknown drug-consumption behaviors in the setting of nonmedical uptake and rarely considers the relationships between substance manipulation, unconventional ROA, and nonmedical substance administration.

Rehabilitation

A third challenge posed by the opioid epidemic is understanding how to help those who suffer from Opioid Use Disorder begin and sustain recovery from drug use. *Opioid Use Disorder* is a chronic disease due to the continued use of opioids that drives adverse emotional states and relapse, leading to clinically significant impairment or distress (Strang et al., 2020; Dydyk, Jain, and Gupta, 2021). This disorder is predominantly treated with opioid replacement therapy/opioid agonist therapy. This therapy consists in replacing the abused opioids with controlled quantities of methadone, buprenorphine, or naltrexone, thus reducing the risk of morbidity and mortality.

The Substance Abuse and Mental Health Services Administration (SAMHSA) [1] is the governmental agency deputed to facilitate patients access recovery services. It sponsors Medication-assisted treatment (MAT), the use of the replacement therapy with the medications mentioned above, in combination with counseling and behavioral therapies, to provide a "whole-patient" approach that includes physical and mental recovery to treating substance use disorders. It has been proven that non-pharmacologic behavioral therapy, e.g., twelve-step programs, peer support groups, mental health counseling, individual and group therapy, is beneficial to successful remission. Recovery presents the patients with many complex physical and mental challenges that typically lead them to periods of exacerbation and remission. Unfortunately, the vulnerability to relapse never disappears for individuals in recovery, and it is likely to put the patient in a stall condition. For this reason, during and after formal recovery treatment, individuals suffering OUD are usually encouraged to participate in *peer support groups*. One of the current issues in aid to rehabilitation is that, unfortunately, persons with OUD are often marginalized by society or under-served by health care services. The marginalization and the barriers to access to health care services like peer support groups may involve accessibility issues, segregation issues but also personal factors; these might include simple time conflicts or more complex ones, like difficulties in sharing feelings in person, privacy concerns, and most importantly, social stigma (Biegel and Song, 1995; Rapp et al., 2006). In addition, the SARS-CoV-2 pandemic containment policies heavily disrupted mobility, in-person contacts, and group gatherings, consequently obstructing access to opioid treatment (Mellis, Potenza, and Hulsey, 2021; Krawczyk et al., 2021). So, despite a recent effort to enhance the availability of remote treatments programs for substance use disorders through telemedicine (Fiacco, Pearson, and Jordan, 2021), virtual meetings (Galanter, White, and Hunter, 2021), and specialized health online fora (MacLean et al., 2015), peer support groups are currently facing many challenges in delivering their services.

1.3 What is missing

The areas of investigation and intervention across the multitude of opioid epidemic studies focus on different levels of temporal, spatial, and population aggregations depending on the task at study. Traditional methods of health surveillance, medical research, and social science research generally involve applying direct observation

[1] https://www.samhsa.gov/

and surveys to shift the attention from the system-wide population level, where data collection is hard to perform, to smaller cohorts where deeper investigations can be conducted. These methods rely on direct human intervention and involve planning data collection and experiments that often require the direct involvement of the population under study. For instance, pharmacovigilance and surveillance on the drugs in circulation is traditionally performed via collecting and analyzing biological samples from patients in a study cohort or via toxicological tests on individuals who died of an overdose. On the other hand, survey methods consist in asking a series of direct questions to the population under study, whether in first person, by telephone, or via online platforms. These legacy methodologies are widely adopted and effective in producing high-quality data. Nevertheless, to ensure good results, the sample of patients must be carefully chosen and often refers to small and specific socio-economic or affinity groups, e.g., college students, schools, addicts in recovery. Hence, these kinds of methods rely either on the capability of performing consistent lab analyses or on the willingness of the users to answer on very personal matters, potentially mining generalizability, and opening up to interpretation biases (Palamar et al., 2019; Palamar, Le, and Mateu-Gelabert, 2019).

Today, as the types and modes of human interactions rapidly evolve with technology, research and interventions in this area could benefit from techniques and data streams that were previously unavailable and which open up new opportunities and practices. In particular, a growing quantity of aspects of our lives now relies on digital technologies that require a continuous creation and fruition of digital data. The availability of large-scale digital data, in turn, may provide new lenses over human behavior at scale, including aspects of behavior that involve opioid consumption. Hence, all the fields of intervention we mentioned, particularly those that use legacy methods, have specific areas that require improvements and could benefit from the new opportunities that arise from the use of advanced computational techniques and novel digital data.

The current public surveillance of the opioid epidemic lacks accuracy and completeness, with estimates that suffer from different reporting infrastructures and miss the contribution of not tested substances. Moreover, it lacks timing due to the significant delay caused by collecting, standardizing, and analyzing data from different sources. For these reasons, in this work, we propose to make use of digital data to extract proxy signals to monitor the opioid epidemic. This novel information could be used in conjunction with conventional methods to inform the existing surveillance systems in an efficient and time-sensitive way.

Like public health surveillance, conventional pharmacological research sometimes lacks specificity due to the small samples that can be studied with traditional techniques, which usually include interviews with drug users. Moreover, due to the evolving nature of drug abuse, pharmacovigilance struggles in spotting unknown nonmedical drug-consumption behaviors and rarely considers the relationships between substance manipulation, unconventional ROA, and nonmedical substance administration. The use of digital data that we propose in this work potentially unlocks the possibility of including thousands of individuals in these studies. Moreover, if properly treated and extracted, digital data could provide the large-scale and fine-grained information on nonmedical drug consumption that is currently missing. Finally, the accessibility to nonpharmacological rehabilitation treatment is still hindered by too many barriers, whether endogenous to the person in recovery or exogenous. In this work, we leverage the novel possibility of connection with peers on online platforms, and we propose the use of social media as a complementary tool to access peer support treatment. This may potentially constitute a positive innovation in the field of aid to rehabilitation, offering new and potentially more accessible ways of receiving support in recovery.

1.4 A digital approach to the opioid epidemic

In the context of the challenges mentioned, a digital epidemiology approach (Salathe et al., 2012) might be extremely valuable to integrate and complement the existing knowledge about the opioid crisis. *Digital epidemiology*, also referred to as *digital disease detection* (Brownstein, Freifeld, and Madoff, 2009a) and *infodemiology* (Eysenbach, 2009) broadly includes the use of the Internet and digital technologies for collecting, aggregating, and processing health-related information that might be used for a variety of purposes, from personal health monitoring to public health surveillance (Correia et al., 2020). Data from a so-called *digital cohort* can be collected leveraging the Internet with the active participation of individuals, as in the case of participatory epidemiology (Freifeld et al., 2010). Participatory systems have been implemented through the use of Web platforms (Paolotti et al., 2014) and signals collected from such systems have been shown to be useful for epidemic forecasting (Zhang et al., 2017). Alternatively, relevant health-related information can be collected passively as a byproduct of platforms designed for different purposes, e.g., from social media like Twitter and Facebook, search engines like Google, or websites like Wikipedia. This is the approach we embrace in this dissertation. Digital data have shown to be helpful in monitoring different infectious diseases from influenza to zika (Brownstein, Freifeld, and Madoff, 2009b; Chunara, Andrews, and Brownstein, 2012; Kass-Hout and Alhinnawi, 2013; Brownstein et al., 2017; Sharma et al., 2017), and recently to Covid-19 (Budd et al., 2020), but also to study complex tasks like drug-drug interactions (Kolchinsky et al., 2015).

Data quality is a potential flaw of using social media-based data instead of traditionally gathered ones. In designing an experiment with traditional methods, researchers can pose well-defined questions with controlled and potentially highly qualitative outcomes, while the analog aspirations using social media data face more significant challenges. The collection of information from textual and multimedia data in social media, especially, has first to address potential issues of representativeness, media coverage, and language usage. Users often use social media in unexpected ways and for different reasons, so the researchers who use the digital epidemiology approach must put a particular effort into validating the proxy signals gathered through online sources against real-world signals. Nevertheless, the use of digital data has its own advantages. By gathering relevant information with a bottom-up unsolicited approach, without directly involving the participants, the digital epidemiology approach has the capabilities of remote sensing minorities and hard-to-reach populations, the community of drug users for instance, without interrupting or interfering with their lives.

In recent years, as many of our social interactions gradually make more use of internet-based communication, the use of social media changed the way drug users socialize, seek information, and share knowledge about the world of drug usage. These new technologies enabled an unprecedented level of connectedness among drug users, allowing them, for instance, to share online warnings of potentially toxic drug batches of heroin containing fentanyl (The Guardian, 2017) and avoid likely overdoses. The signals point at "Reddit: the front page of Internet" (Reddit, 2018) as a promising digital source of information for monitoring the opioid crisis.

Social media also assume a role of particular importance in reducing stigma and discrimination for individuals suffering from OUD and other socially stigmatized conditions (Betton et al., 2015). This new type of connection enables those who suffer from substance-use-related conditions, mental health issues (Choudhury and De, 2014), sex/gender-related issues (Nobles et al., 2018; Saha et al., 2019), and physical health issues (Enes et al., 2018), to spontaneously engage with online communities discussing these topics when no other options are available and offer an alternative point of view to standard in-person interactions. People in need of peer support for OUD, in particular, are increasingly finding a safe place to share their experiences in online social media platforms that provide pseudonymity like Reddit (Bunting et al., 2021; Andalibi et al., 2016; Sowles et al., 2018). In recent years, a growing quantity of computational studies has been carried out in the fields of opioid use disorder and opioid use recovery, especially using Reddit as a data source. The Research community has used digital and social media data to perform various tasks, including detecting drug abuse (Hu et al., 2019; Prieto et al., 2020), forecasting opioid overdose (Ertugrul, Lin, and Taskaya-Temizel, 2019), studying transition into drug addiction (Lu et al., 2019), predicting opioid relapse (Yang, Nguyen, and Jin, 2018), and discovering previously unknown treatments for opioid addiction (Chancellor et al., 2019b).

1.5 Contributions and thesis outline

This dissertation focuses on studying the phenomenon of nonmedical opioid use in the United States of America by leveraging digital traces gathered on social media. In particular, we focus on mining and treating data available on Reddit, a major social media platform in the US, to answer several relevant questions on three crucial aspects concerning the opioid epidemic. Specifically, we focus on *public health monitoring*, *pharmacovigilance*, and *aid to rehabilitation*. With this work, we provide quantitative results on different aspects of the opioid epidemic that offer a novel, broad, and yet detailed data-driven perspective on the subject. We believe that focusing on these orthogonal topics may result in a comprehensive understanding of this complex phenomenon allowing the reader to understand three different but complementary aspects: the gravity and diffusion of the crisis, the complexity of drug administration and consumption in a nonmedical setting, and the impact of personal and collective behavior on rehabilitation.

This work collects and expands two published research studies carried out during the course of the Ph.D. program of the candidate (Balsamo, Bajardi, and Panisson, 2019; Balsamo et al., 2021), and one work recently submitted to a top-tier international journal. In this work we develop and apply state-of-the-art information retrieval, Machine Learning, and Natural Language Processing techniques to deal with the complexity of the extraction, the validation, and the analysis of relevant information from a data source as big and rich as Reddit. These techniques are introduced and explained in detail throughout the dissertation. The structure of the dissertation, the main results obtained, and the techniques implemented are summarised in the following.

In Chapter 1, we first introduced the reader to the opioid crisis in the US. We focused on the unfolding of the crisis and its challenges, and we discussed the areas of intervention that are addressed in this work. Next, we introduced the Digital epidemiology approach used in this research, outlining its differences with traditional approaches.

In Chapter 2, we describe in more detail the context of this work. We report a detailed review of related work, divided by areas of interest. Then, we present the structure of Reddit and the uses of Reddit data for research, and we describe the dataset employed for the experiments in this dissertation. Finally, we discuss ethical and privacy considerations.

In Chapter 3, we focus on public health monitoring aspects of the epidemic. We identify a large cohort of Reddit users exhibiting explicit interest in opioid consumption, and we estimate the geographical distribution of the interest-in-opioids phenomenon at the US State level. In this chapter, we present an information retrieval algorithm suitable to navigate the many parts of Reddit to identify the subspaces of discussion relevant to our topic. Thanks to regular expression, we infer the geolocation of 1.5 million Reddit users and estimate the prevalence of interest in opioid and opiate consumption at the US State level. These results produce a novel indicator of interest-in-opioids with information not entirely encoded in the standard health surveillance system, showing how Reddit may constitute a valuable resource for public health monitoring.

In Chapter 4, we leverage the content shared on the platform to gain relevant pharmacological insights on nonmedical opioid use. We study the temporal unfolding of the adoption of opioid substances and bring evidence of complex patterns of nonmedical consumption that include how the drugs are tampered with and administered. To overcome the obstacle of the widespread use of slang on social media and gain additional knowledge on the terminology used in the context of nonmedical opioid use, in this chapter we present a novel vocabulary-expansion methodology based on word embedding. With our method, we find alternative slang, colloquial, and nonmedical terms referring to opioid substances, routes of administration, and drug-tampering methods, which we supply to the public as structured vocabularies. Leveraging the acquired terminology, we estimate the prevalence and temporal unfolding of the adoption of substances and routes of administration. Finally, we provide a measure of the strength of association between opioid substances, routes of administration, and drug tampering.

In Chapter 5, we investigate aspects related to the aid to rehabilitation. We analyze the social interactions of thousands of Reddit authors during the start of the recovery from opioid use to investigate the potential of Reddit as an online peer support group. In this chapter, we use machine learning to identify a large number of Reddit users recovering from opioid use, and we estimate the day on which these users started rehabilitation. Then, we leverage recently developed natural language processing tools to characterize the content shared on the platform, in a time window ranging from two months before to two months after the start of recovery, according to ten social dimensions of conversation and relationships .We uncover that a particular recovery-oriented community on Reddit exhibits many characteristics similar to in-person peer support groups by offering peer support, acknowledgment, and encouragement. Moreover, we find that the supportive behavior of this community nudges the recovering authors to change personal behavior, promoting the abandonment of the opioid-related community in favor of recovery-oriented relationships. Finally, we find that recognition, acknowledgment, and the exchange of knowledge and support are the most relevant factors in driving the engagement and attachment of the users to the recovery community.

Finally, in Chapter 6 we draw the conclusions and discuss the potential implications of our work. We outline that thanks to innovative techniques and novel data sources, it is possible to provide a new perspective on pressing and multi-faceted issues like the opioid epidemic, with the hope of possibly informing and helping public health stakeholders. We discuss how our work might inspire the public institutions to use advanced techniques on digital media for remote sensing the evolution of health-related issues, understanding complex health-related behaviors of hard-to-reach populations, and informing harm reduction policies and interventions to favor successful rehabilitation.

Chapter 2

Background

2.1 Public health monitoring

Every year, the Centers for Disease Control and Prevention provides the data collected by the different States of the Union. These data are reported in the form of aggregate statistics like counts, rate maps, and rate changes for some fundamental dimensions, like the prescribing practices by State and the drug Overdose Deaths (CDC. Centers for Disease Control and Prevention, 2019). Changes in drug overdose death rates and drug overdose rates are differentiated by the main categories of opioids involved, such as the aggregate of all prescription opioids, the total of synthetic opioids like fentanyl analogs, and heroin, the most common illicit opiate. These data are available to the public using the *Wide-ranging online data for epidemiologic research* (WONDER) portal (National Center for Health Statistics, 2020), managed by the CDC and the National Center for Health Statistics. An intrinsic bias that makes the estimates of the CDC not entirely accurate is, for instance, the way in which each State reports the overdose deaths. Drug overdoses deaths are confirmed by clinical tests assessing the presence of drug poisoning as classified by the International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10) (World Health Organization, 2004). In reality, this process presents many issues due to the unequal development and coverage of the surveillance systems across States and different availability of testing (Landen et al., 2003; Ruhm, 2017). In addition, the underlying phenomenon of drug consumption suffers from low specificity of the drugs in some areas of the country (Hedegaard et al., 2014) and the overdose deaths involving opioids show very heterogeneous geographical patterns (Seth et al., 2018). Combined, all these aspects make the official surveillance statistics not entirely accurate and often not timely. A complementary way to investigate these phenomena is by field studies through ethnographic approaches and structured interviews. Sadly, these methods require an exceptional effort in order to gather insights from firsthand users (Mars et al., 2014) or subjects under opioid substitution maintenance treatment (Bawor et al., 2015; Sordo et al., 2017), and are often limited to small sample sizes ranging from tens to hundreds of individuals. A few recent studies investigated the temporal unfolding of the opioid epidemic in the United States by leveraging complementary data sources different from the official CDC data (Kolodny et al., 2015; Phalen et al., 2018; Zhu et al., 2019; Rosenblum, Unick, and Ciccarone, 2020; Black et al., 2020). Among the few social-media-based analyses measuring trends in the context of the opioid epidemic, Pandrekar et al. (Pandrekar et al., 2018) considered 51k posts taken from the Reddit community *r/opiates* and spanning from 2014 to 2017 to provide the raw count of mentions of opioids over time. For these reasons, in Chapter 3 we leverage Reddit data to depict the geographical representation of a synthetic signal that partially encodes the official data about opioid prescriptions and opioid overdose deaths.

2.2 Pharmacovigilance

Many traditional medical, pharmacological, and public health studies investigated the adoption of prescription opioids in the context of nonmedical use (McCabe et al., 2007; Katz et al., 2008; Butler et al., 2008; Butler et al., 2011; Agnich et al., 2013; Amsterdam and Brink, 2015; Curtis et al., 2019; Richards et al., 2020). These works usually estimate the prevalence of routes of administration for nonmedical prescription opioids (Butler et al., 2008; Katz et al., 2011; Kirsh, Peppin, and Coleman, 2012; Gasior, Bond, and Malamut, 2016) and opiates (Ciccarone, 2009; Carlson et al., 2016), sometimes considering also less studied substances, like the codeine (Agnich et al., 2013). However, these studies rarely consider less common ROA, such as *rectal*, *transdermal*, or *subcutaneous* administration (Gasior, Bond, and Malamut, 2016), usually overlooked as considered minor and negligible ROA, with rare exceptions for rectal administration (Coon et al., 2005; Gasior, Bond, and Malamut, 2016),leaving the mapping of nonmedical and nonconventional administration behaviors greatly unexplored (Rivers Allen and Bridge, 2017; McCaffrey et al., 2018). Few studies provide insights into routes of administration for heroin (Ciccarone, 2009), and scarce literature investigated the potential of health-related risks to nonmedical use of opioids (Young, Havens, and Leukefeld, 2010) and unexpected ROA (Strang et al., 1998). Many of these studies (Katz et al., 2011; Kirsh, Peppin, and Coleman, 2012; Gasior, Bond, and Malamut, 2016) acknowledge that the intentional chemical or physical alteration of medications, known as drug tampering (Mastropietro and Omidian, 2014), is an essential constituent of drug abuse. However, to the best of our knowledge, no large-scale empirical studies unveiled the relationships between substance manipulation, unconventional ROA, and nonmedical substance administration. While the traditional pharmacological studies offer estimations on the adoption of prescription opioids with data gathered through surveys (McCabe et al., 2007; Katz et al., 2008; Agnich et al., 2013) and through digital databases (Butler et al., 2008; Butler et al., 2011), in Chapter 4 we analyze the content of the conversations about opioid usage to provide fine-grained estimates about opioid consumption. We estimate substance adoption for nonmedical use of opioids, including not just prescription opioids but all illicit opiate substances. We study the diffusion of the various conventional and unconventional Routes of Administration and uncover the use of drug tempering methods.

2.3 Rehabilitation

As a growing number of millions of individuals are suffering from Opioid Use Disorder (Substance Abuse and Mental Health Services Administration (SAMHSA), 2021), the research community and public health institutions like the SAMHSA continuously investigate on better ways to promote harm-reduction and rehabilitation strategies. The most effective short-term harm-reduction strategies are to make the use of opioid antagonists easily available and widely accessible to recovery groups and individuals affected by OUD. Medication-assisted treatment, however, has been proven more effective in combination with counseling and behavioral therapies, such as *peer support groups*. This type of nonpharmacological treatment is based on *peer support*, which is the assistance shared among nonprofessional individuals with similar conditions to achieve and sustain recovery (Tracy et al., 2016). Compared to professional clinical advice, *peer support* has the possibility of reaching a deeper level of trust, understanding, and acceptance due to the communal background and shared experience of the individuals (Mead and MacNeil, 2006). Peer support groups have been extensively proven effective in treating substance use and mental-health-related conditions (Reif et al., 2014; Tracy et al., 2016; Bassuk et al., 2016). In addition, studies reveal that people who receive this kind of treatment show benefits in reduction of substance use and reduction of relapse rates while incentivizing other peer users in treatment engagement (Choudhury and De, 2014; Sharma et al., 2020). Key components of such groups are *social support*, i.e the existence of positive psycho-social interactions with others with whom there is mutual *trust* and concern (Sarason et al., 1983), experiential *knowledge*, and peer mentoring (Mead, Hilton, and Curtis, 2001). These groups can be helpful, especially during the initial stages of recovery, as they provide encouragement to endure through community reinforcement and empowerment and by promoting self-esteem in participants (Reif et al., 2014). Although the initial involvement in a peer support group is primarily instrumental, the reason for staying is usually aimed at maintaining social support and developing self-esteem (Schutt and Rogers, 2009). Active engagement in peer support groups has shown to be a key predictor of recovery (Donovan and Wells, 2007; Best and Lubman, 2012) and sustaining recovery (Etheridge et al., 1999). As such, individuals with higher attendance levels showed statistically significant improvements over time in self-esteem–self-efficacy and community activism–autonomy (Vayshenker et al., 2016). Overall, higher social engagement is moderately associated with reduced relapse rates and increased treatment retention (Reif et al., 2014). Alongside the physical struggle posed by drug detoxification, such as cravings and withdrawal symptoms, a further challenge to successful substance use recovery is managing the uncertainties of a drastic change of lifestyle (Reif et al., 2014; Tracy et al., 2016; Bassuk et al., 2016). Existing literature suggests that the mechanism of recovery is a process of *social group change* and *social identity change* (Best et al., 2016). A strong supportive network of relationships with others is recognized to play a crucial role in managing the uncertainties of drastic changes and transitions in someone's life. From these relationships, people gain vital support when such a transition is particularly challenging, as in the case of recovery from addiction. In the process, the identity of a person shifts from being characterized by the membership of a group whose norms and values revolve around substance use to being defined by membership of a new group whose norms and values encourage recovery. Hence, a crucial step for a successful remission of a subject is a "public renegotiation" that starts with the public announcement of his intention to change his lifestyle (Stall and Biernacki, 1986) and continues with stepping away from ones' drug-using networks to sustain the engagement with supportive relationships of recovery (Haslam et al., 2016). Unfortunately, the SARS-CoV-2 pandemic containment policies heavily disrupted in-person meetings, consequently obstructing access to opioid treatment (Mellis, Potenza, and Hulsey, 2021; Krawczyk et al., 2021). Despite the availability of some remote-based treatments service, individuals in need of peer support are still facing many social and accessibility obstacles. As discussed, social media now offer all these individuals a new chance to connect with online communities of likely individuals. With its unique characteristics, Reddit is increasingly becoming a reference point in this regard (Andalibi et al., 2016; Sowles et al., 2018; Bunting et al., 2021), and individuals in substance use recovery can refer to several specialized subreddits, such as the `r/opiates` and the r/OpiatesRecovery communities. A few research studies used computational techniques to investigate the topic of opioid use recovery. Researchers used the data taken from a specialized health online forum, Medhelp's *Forum77* to examine the activity and the linguistic features of the forum across the phases of different phases of the recovery process (MacLean et al., 2015). Chancellor et al. (2019b) used the content of the opioid-related communities on Reddit to spot alternative substances used for helping in opioid use recovery based on word embedding on textual features. Others tested machine learning techniques to quantify the propensity of starting recovery (Eshleman et al., 2017) or of risk of relapsing (Yang et al., 2019) based on the sentiment expressed by the authors or other linguistic features. Except for the work of D'Agostino et al. (2017), which provided some qualitative evidence of DSM-5 criteria (American Psychiatric Association, 2013) for Opioid Use Disorder in 100 comments taken at random from the r/OpiatesRecovery community, no previous work has investigated the therapeutic potential of Reddit for opioid use recovery. Moreover, no previous large-scale study classified and quantified the type of supportive social interactions that might be found in this community. In Chapter 5 we answer this question by analyzing the type and the evolution of social relationships which form in this group, showing how they impact the behavior of the users on the platform.

2.4 Reddit

2.4.1 Structure of Reddit

Reddit [1] is a social content aggregation website on which users can post, comment, and vote on content on a large variety of topics. Since its foundation in 2005, this emerging social media platform has constantly been growing in the volume of posts and the number of users, claiming 52 million daily active users in October 2020 (The Wall Street Journal, 2020) with 44 percent growth year over year. The Reddit website is visited by users worldwide, but with around 38% of traffic coming from the US, its user base is predominantly based in North America. At the moment of writing, *Reddit.com* is the 8th most popular website in the United States and the 23rd in the World (Alexa, 2022). Reddit is "a network of communities where people can dive into their interests, hobbies and passions" and it is structured into independent sub-communities called *subreddits*, identified by a r/+name handle e.g. r/AskReddit, r/politics, r/gaming. These forum-like communities are entirely user-generated and user-moderated and are often dedicated to the discussion of specific topics of interest (Medvedev, Lambiotte, and Delvenne, 2018). Reddit users, called *redditors*, can create and moderate new subreddits on any topic of choice, or they can post a submission or a comment on already-existing subreddits, where their content is upvoted or downvoted by other users. The order and the relevance of the content on the platform, i.e., either inner to specific subreddits or on the collector of the most trending posts called *front page*, is entirely driven by the votes of the Redditors, in a bottom-up approach. A schematic representation of the structure of Reddit, its subreddits, and its threads of posts is represented in Figure 2.1.

Due to fair guarantees of anonymity, no limits on the number of characters in a post, and the possibility to infinitely create new subreddits to debate on virtually any topic, this platform is often used to uninhibitedly discuss personal experiences (Manikonda et al., 2018). Moreover, given the ease of registering with a "throwaway"

[1] www.reddit.com

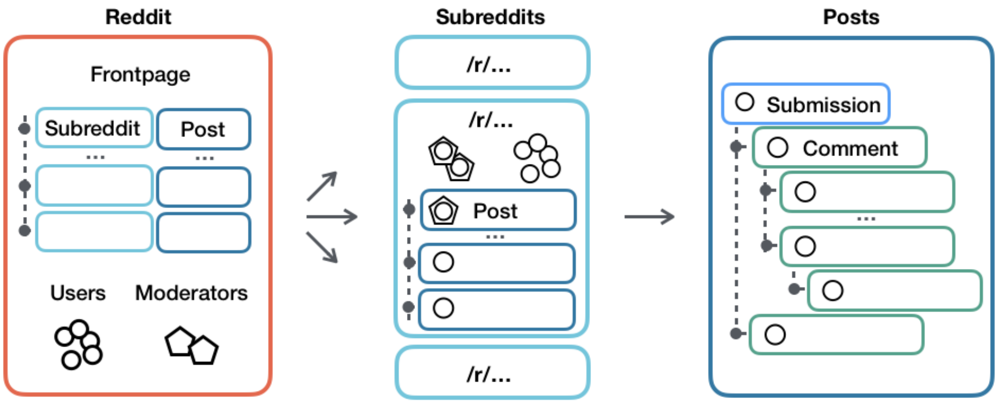


FIGURE 2.1: Schematic representation of the structure of Reddit. Reddit's most common access point is the front page, where the most relevant content of the moment is collected. The users can post on already-existing subreddits or create new ones. Users can either create a new thread via submission or indefinitely expand the conversation tree by commenting on an existing thread in a subreddit. The level of content moderation in a subreddit is solely decided by its moderators.

account, Reddit is often used to ask questions and receive support on sensitive personal issues and to discuss topics otherwise considered socially unacceptable or unsuitable for the mainstream (Manikonda et al., 2018).

However, navigating such a massive platform and finding areas of specific interest is usually cumbersome since topics are constantly evolving and are self-organized. To grasp the complexity and the variety of the topics treated on Reddit, we report in Figure 2.2 a pictorial representation of the macro areas of Reddit in 2016. In this graph, the nodes represent the subreddits with at least 1000 authors, and the weight of the edges connecting two nodes represent the numbers of authors who wrote submissions or comments in both subreddits. The construction of this network involves around 390k subreddits and over 12.8 million Reddit authors. By applying the algorithm by Coscia and Neffke (2017) to the raw graph with 4651 nodes and 171442 edges, we extract the Noise Corrected backbone of the network, resulting in a network of 3471 nodes and 7990 edges. In order to identify the macro clusters "of interests" on the platform, we apply the Louvain clustering algorithm based on Modularity by Blondel et al. (2008), and color-code the nodes based on cluster belonging. We report in the figure only the largest connected component of the graph, which includes 97% of the nodes.

2.4.2 Research on Reddit

In recent years, Reddit has proven to be suitable for a variety of research purposes (Baumgartner et al., 2020), ranging from the study of user engagement and interactions between highly related communities (Tan and Lee, 2015; Hessel, Tan, and Lee, 2016) to post-election political analyses (Barthel, 2016). Also, it has been helpful to study the impact of linguistic differences in news titles (Horne and Adali, 2017) and to explore recent web-related issues such as hate speech (Saleem et al., 2017) or cyberbullying (Rakib and Soon, 2018). As already mentioned, thanks to its unique characteristics, Reddit constitutes a nonintrusive and privileged data source to study a variety of sensitive topics such as mental health (Choudhury and De, 2014), weight loss (Enes

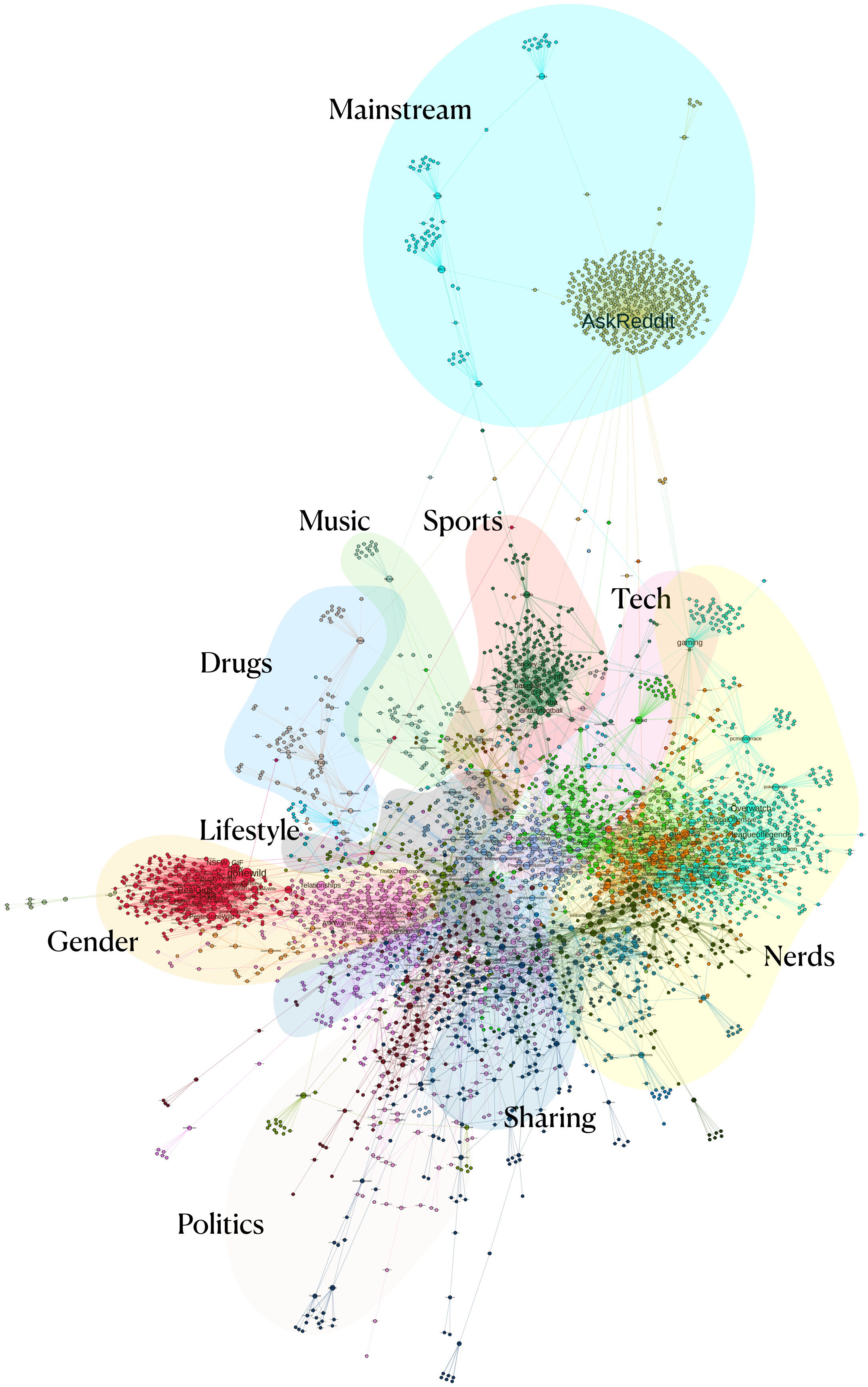


FIGURE 2.2: Reddit's network of subreddits. In this graph, the nodes represent the subreddits, and weighted edges represent the numbers of authors in common. The size of the nodes and the thickness of the edges are proportional to the degree of the node and the edge weight, respectively. Nodes of the same color belong to a common cluster "of interest".

et al., 2018), and gender-related issues (Saha et al., 2019). Naturally, in addition to these sensitive topics, this data source is very valuable to provide insights about the opioid epidemics (Park and Conway, 2017) and on nonmedical use of substances at large (Lu et al., 2019; Chancellor et al., 2019b).

2.4.3 The Pushshift Reddit Dataset

The wealth of data generated on Reddit is accessible for research purposes in two principal ways. The first one is to pull data through the Reddit API [2]. Users logged in on Reddit can ask the platform for an authorization token, with which they can make requests using a GET procedure and pull textual data from Reddit in JSON format. Alternatively is possible to use the Python Reddit API Wrapper (PRAW) (Boe B., 2012), a purpose-built library for interacting with the Reddit API using python. This method makes it possible to filter and select only the relevant content to one's research. The major drawback of this method is not having the complete Reddit dataset unless one chooses to download it via request piece by piece. The second way of gathering Reddit data is to download dataset batches containing all comments or submissions produced on Reddit in a given month. These data are downloaded, standardized, and compressed in large JSON files by the Reddit user `u/stuck_in_the_matrix`, an alias for Jason Baumgartner, and provided to the public through the Pushshift website [3]. This massive dataset, also available for consultation using Google BigQuery and its own API[4], contains the list of all submissions and comments published in Reddit since 2007 (Baumgartner, 2015) and is maintained monthly by adding recent entries. Gaffney and Matias (2018) acknowledged that the dataset up to 2018 is not 100% complete and it contains some gaps, but these are very small from 2016, missing only around 1% data per month. The advantage of using this dataset for research purposes is the possibility to conveniently download the whole content of Reddit to perform analyses at scale. Moreover, since each data batch corresponds to the copy of the content at the time of pulling it from Reddit, generally a gap that goes from a few days to a few weeks, this dataset includes original parts of the content that may have been deleted afterward. On the other end, the main disadvantage of this dataset is the time lag with which the data batches are published, an issue that is not present when using the Reddit API. In addition, this last approach requires considerable disk space to store the data and a suitable computational structure to parse the massive amount of text files.

In this work, we collected and used the data from the Pushshift Reddit repository. The whole dataset, collected over the years of the Ph.D. program, spans from 2014 to 2019, amounting to a total of 123Gb of stored submissions and 688Gb of stored comments. Figure 2.3 reports the size of the datasets for each year. The files are compressed with the bzip2 algorithm, which offers a compression ratio ranging from 16% to 19%; therefore, the estimated total size of uncompressed data corresponds to approximately 4.5Tb. To parse and analyze this massive dataset in an efficient and parallel way, we used PySpark [5] to interface Apache Spark in Python. Throughout the dissertation, we use different parts of the dataset for the various projects, depending on the availability of the data at the time of the experiments and on the type of analyses to perform.

[2] https://www.reddit.com/dev/api/
[3] https://files.pushshift.io/reddit/
[4] https://github.com/pushshift/api
[5] https://spark.apache.org/docs/latest/api/python/

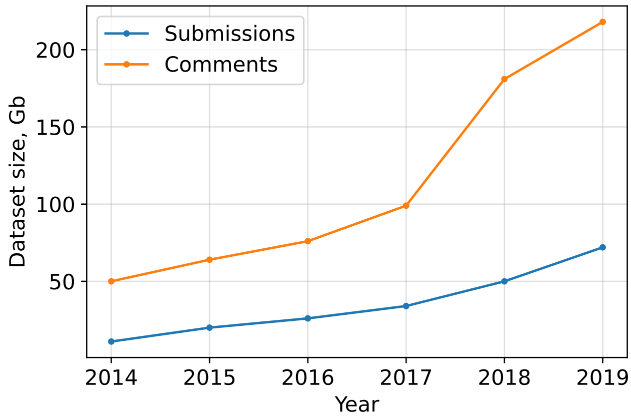


FIGURE 2.3: Size of the Reddit datasets for Submissions and Comments per year, expressed in Gb. The numbers consider the size if the datasets as compressed with bzip2 algorithm with a compression ratio ranging from 16% to 19%

2.5 Ethics and Privacy

The information publicly shared by the users on Reddit might include the location, gender, health status, and other sensitive personal information, as well information providing indicators of personal preferences and interests. The sensitive nature of these data calls for ethical considerations and the highest standard of privacy preservation. In this work, we followed the guidelines by Eysenbach and Till (2001), which describe recommendations to conduct medical research with user-generated online data ethically. We also relied on the ethical considerations of a more recent body of work from the computational social science community dealing with sensitive data gathered on social media (Moreno et al., 2013; Hswen et al., 2018; Saha et al., 2019; Chancellor et al., 2019a; Ramírez-Cifuentes et al., 2020). First, in this work, the researchers had no interaction with the users and no interest in harming any. Second, all the analyses are performed and reported in the spirit of knowledge, prevention, and harm reduction. Every result intends to provide aggregated estimates, aiming at research purposes. Our work does not feature any quotes or information that focuses on single authors; the reported examples, when present, are paraphrased to avoid the possibility of recovering the original message. Third, at the time of posting, the users in our study were fully aware of the public nature and free accessibility of the content they posted since the subreddits under investigation are of public domain, are not password-protected, and have thousands of active subscribers. Moreover, Reddit offers pseudonymous accounts and strong privacy protection, making the possibility of recovering a user's true identity very unlikely. Nevertheless, to further protect the privacy and anonymity of the users in our data set, all information about the authors' names is anonymized before using the data for analysis. Following the directives in Eysenbach and Till (2001), our research did not require informed consent.

Chapter 3

Mapping the opioid epidemic

3.1 Scope

In this chapter, we tackle the problem of monitoring the opioid epidemic using Reddit proxy data. In particular, we aim at identifying a large cohort of Reddit users exhibiting explicit interest in opioid consumption, estimating their geographical distribution across the US States. Then we provide maps of the interest-in-opioids rates at the US State level. However, navigating a massive platform like Reddit to acquire this kind of information poses many technical challenges. For this reason, in this chapter, we present a general-purpose Information Retrieval algorithm to identify regions of interest when conducting epidemiological surveillance and monitoring on social media. Then, we apply it to finding subspaces of discussion related to interest in opioids on Reddit. In doing so, we also provide the public with an open domain-specific vocabulary related to opioid discussions.

Finding areas of specific interest on Reddit is usually non-trivial since the topics on the platform are created by users, self-organized, and self-moderated, and the comments are sorted through users' interactions. This lack of structure delegates to the users the task of finding relevant topics, exploring new subreddits by word of mouth, by links to other subreddits, or via the basic search feature embedded in the platform. Since the users collectively generate the content on the platform, there is not a blueprint of Reddit to perimeter the area under study, nor an index of the subreddits associated with each topic. For these reasons, a few studies attempted to extract meaningful maps or suitable embedding spaces to navigate the platform (Olson and Neal, 2015; Martin, 2017).

We approach the issue of selecting subreddits relevant to a specific topic as an Information Retrieval (IR) problem. In this setting, it is ideally possible to retrieve all the relevant topic-specific documents by expressing a limited set of known keywords, a set that the Information Retrieval process itself might enrich. Language models (Ponte and Croft, 1998; Schütze, Manning, and Raghavan, 2008; Croft and Lafferty, 2013) tackle this problem using a probabilistic approach, The underlying idea of these works is that words that are relevant for a given topic would be more likely to appear in a relevant document. While language modeling is not a common approach for ranking documents collected from certain social media –especially from Twitter, where more elaborated IR approaches are needed to resolve the sparsity of short texts of the tweets (Naveed et al., 2011) –, this approach might be suitable for Reddit. The aggregate of the posts of each subreddit, in fact, can be seen as very rich documents from which topic-specific word distributions can be built. When initiating an Information Retrieval process, the set of keywords expressed by who performs the query may not be exhaustive. For instance, the set of query terms may not include some lemmas, yet unknown, very specific to the language models of the corpus of documents, but very relevant to the target topic. Hence the necessity of query expansion techniques contextual to the document retrieval process. Relevance feedback (Rocchio, 1971) and pseudo-relevance feedback (Buckley et al., 1995) are standard approaches for query expansion; many of these approaches use human judgment to manually select a subset of the top retrieved documents and use them to expand the query. More recently, *word embeddings* have been used to expand the query with terms that are semantically similar to the query terms (Kuzi, Shtok, and Kurland, 2016). Research works on IR based on language modeling incorporate information on term proximity (Ermakova, Mothe, and Nikitina, 2016) to address the automatic query expansion problem or use approaches based on Information Theory, like exploiting the *Kullback-Leibler distance* for query reweighing (Carpineto et al., 2001) and for training local word embeddings (Diaz, Mitra, and Craswell, 2016). In this chapter, we address these problems by presenting our IR procedure to collect relevant documents while enriching the set of query keywords.

3.2 Data preparation

In this chapter, we use the union of all submissions and comments produced on Reddit during 2016 and 2017 for a total of 1,98 billion entries. First, we filter the dataset via the size of the subreddits, retaining only the subreddits with at least 100 entries. The filtering operation results in a set of over 1.97 billion entries with 74 thousand distinct subreddits and over 15.7 million unique users. The text of each entry is parsed and tagged using the spaCy NLP library (SpaCy, 2020) v1.9.0. For the part-of-speech tagging (POS), we use a greedy averaged perceptron model (Honnibal and Johnson, 2015). Finally, lemmatization is applied to each POS tag; the English lemmatization data is taken from WordNet (Miller, 1995), and lookup tables are taken from Lexiconista [1]. After the lemmatization of all terms, we select those that appear at least 100 times in the corpus, resulting in a vocabulary containing 762,746 lemmas.

3.3 Identifying a digital cohort

3.3.1 Document ranking and query expansion

As previously discussed, the wealth of information contained in Reddit data is not readily available and has to be thoroughly mined. This section describes an iterative methodology of semi-automatic retrieval of documents in heterogeneous corpora, in which human intervention is as little as possible. It is worth stressing that our approach is general and fully unsupervised. However, due to the sensitive purpose of this work on public health monitoring, we added a human-in-the-loop to include domain expert knowledge in the process and reach better results. On the other hand, a domain expert alone without the aid of the algorithmic pipeline for document ranking and query expansion would have been hopeless in navigating the Reddit world by hand. The steps of the algorithm are formally reported in Algorithm 1 and visually summarized in Figure 3.1. The structure of the algorithm is the following. We start with a small set of keywords Q provided by the user, also referred to as *query* in the following. At each iteration of the algorithm, we select documents that are relevant to the query, and we enrich the set of *query* terms with the most informative terms in documents selected. We repeat the procedure until we arrive at a stable

[1] http://www.lexiconista.com/datasets/lemmatization/

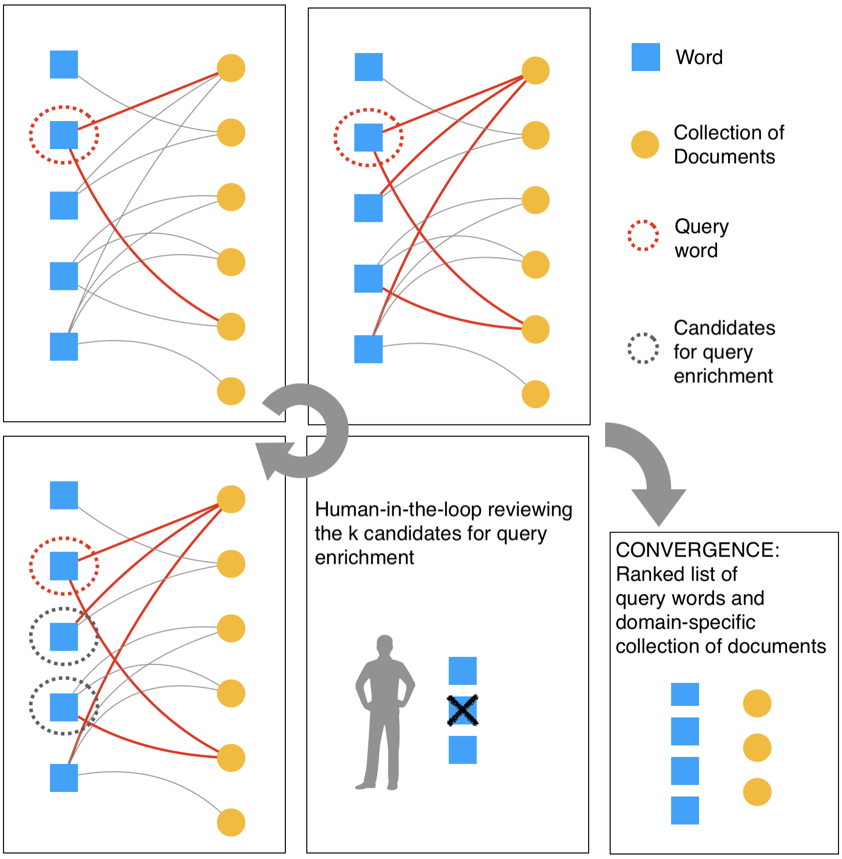


FIGURE 3.1: Visual schema of the query expansion procedure.

list of documents and query terms. While this methodology works well on Reddit in the domain of topics related to the opioid epidemics (see Section 3.3.2), it is also sufficiently general to be used for other Information Retrieval tasks and might be valuable for different epidemiological research questions.

Here we report the whole procedure in detail. First, we create a general vocabulary **V** by collecting terms from the entire corpus of documents in a bag-of-words fashion, i.e., including all terms regardless of their order in the documents. We compute the probability of occurrence of a term w in the entire corpus C as the ratio $p_C(w) = f_C(w) / \sum_w f_C(w)$ between its raw count $f_C(w)$ in the corpus and the total number of words in the corpus. Let us also define the regularized marginal probability of occurrence of term w in a document d as

$$p_d(w) = \frac{f_d(w)}{\sum_w f_d(w) + \alpha} + p_C(w). \tag{3.1}$$

where $f_d(w)$ is the count of term w in document d. In the case of corpora with very heterogeneous document sizes, the regularization term α is added to control "the size" of the language model of the documents. In doing so, small documents will result in small marginal probabilities. In our experiments, we use $\alpha = 10^4$, so documents with a total number of words lower than 10^4 have "flattened" probabilities in their language model. Adding $p_C(w)$ to the marginal probability of term w reduces the impact of rare or absent words in a document. As such, only words that are more likely to appear in the document will impact the document's ranking. The use of these two regularization terms, α and $p_C(w)$, are effective in low-count scenarios

Algorithm 1: IR steps for document ranking

Input: Corpus C, query Q
Parameters: n, m, α
Initialize the vocabulary $\mathbf{V}$;
foreach *word* $w \in \boldsymbol{V}$ **do**
  calculate $p_C(w)$;
  foreach *document* $d \in C$ **do**
    calculate $p_d(w)$;
$Q_{new} \leftarrow Q$;
$K_{new} \leftarrow \emptyset$;
repeat
  $Q \leftarrow Q_{new}$;
  $K \leftarrow K_{new}$;
  $R_d \leftarrow$ Rank documents using score$(d \mid Q, C)$ (Eq. 3.2);
  $K_{new} \leftarrow$ top n documents in R_d;
  $R_w \leftarrow$ Rank terms using score$(w \mid K_{new})$ (Eq. 3.3);
  $Q_{candidate} \leftarrow$ top m terms from R_w;
  $Q_{new} \leftarrow$ manual selection of terms in $Q \cup Q_{candidate}$;
until $Q = Q_{new}$ *and* $K = K_{new}$;
Output: R_d, R_w

and have a negligible impact for words with high probability in a specific document, or in the case of documents with a complex language model.

As a relevance criterion, we assume that query terms are more likely to appear in the document relevant to the query and less likely to appear in the general corpus. With this intuition, a document will be relevant in the context of the query if it contains as many query terms –that are more likely to appear in the document than in the general corpus–. To implement this, we evaluate

$$\text{score}(d \mid Q, C) = KLD_Q(p_d, p_C) = \sum_{w \in Q} p_d(w) log \frac{p_d(w)}{p_C(w)} \tag{3.2}$$

which is the total contribution of the query terms in the *Kullback-Leibler divergence* between the document and the whole corpus C.We consider the top n documents ranked by relevance as measured by Equation (3.2) as the *set of relevant documents* K.

Once n is chosen and K obtained, we assign a score to each term in order to enrich the query terms Q, based on the logarithm of the likelihood ratio

$$\text{score}(w \mid K) = \sum_{k \in K} log \frac{p_k(w) + p_C(w)}{p_C(w)}. \tag{3.3}$$

When the term w is more informative in the document than in the general context, i.e., whenever the maximum likelihood estimate $p_k(w)$ of a term in a relevant document is higher than its estimate in the general context $p_C(w)$, its contribution to the score for ranking terms will be high and positive. Conversely, whenever a term is less likely to appear in the document than in the general context, its contribution to such a score will be minor, highlighting that it is of common use or not simply relevant to the target context. We consider the top m terms ranked by Equation (3.3) as a set of candidate query terms $Q_{candidate}$. Then we create a new set of query terms Q_{new} as the union of terms of the previous query Q with a subset of previously unknown relevant terms in $Q_{candidate}$ selected with the supervision of an expert.

The entire pipeline can be iteratively evaluated with the newly enriched set of query terms, Q_{new}, selecting each time a new set of relevant documents K_{new} until convergence. We reach convergence if no new documents are added to the top n documents, and no new relevant terms among the top m can be added to Q. These steps are summarized in Algorithm 1, and the document ranking resulting from the last iteration of the algorithm is used to select the most relevant documents.

3.3.2 Opioid related subreddits and digital cohort

We assume that authors who post content in a subreddit related to a particular topic are *interested* in that topic. Therefore we consider all authors participating in threads on subreddits related to nonmedical opioid consumption as those *interested-in-opioids*. We discover such subreddits by applying the algorithm described in Section 3.3.2. After the data preparation steps described in Section 3.2, we start from a list of opioid-related keywords $q =$ `[fentanyl, oxycodone, suboxone, morphine]`. From the first round of extractions, we select the top $n = 10$ subreddits `r/suboxone`, `r/fentanyl`, `r/Opiatewithdrawal`, `r/TarkovTrading`, `r/heroinaddiction`, `r/ChronicPainPlayhouse`, `r/OpiatesRecovery`, `r/opiates`, `r/Methadone`, `r/PoppyTea`. Then, we proceed with the iterative procedure of query enrichment and document ranking, considering as relevant terms only those related to opioid drug names, i.e. including chemical names (e.g. *oxycodone*), brand names (e.g. *Percocet*) and street slang (e.g. *percs*). In this phase, we discard drugs compounds that might be abused together with the opioids, like the benzodiazepines, but are not in the opioids domain. For our specific task, we reach convergence after three algorithmic rounds. The final set K of *opioid related subreddits* used in this paper is `r/fentanyl`, `r/suboxone`, `r/Opiatewithdrawal`, `r/Methadone`, `r/opiates`, `r/pillhead`, `r/lean`, `r/ChronicPainPlayhouse`, `r/heroin-addiction`, `r/OpiatesRecovery`. Figure 3.2 (top) shows the final ranking score for the subreddits, plotted against their size in terms of the number of words. The most relevant subreddits are all visible in the top part of the figure. Finally, we select our *digital cohort* of user *interested-in-opioid consumption* by including all the 37,009 users who posted on the set of opioid-related subreddits during 2016 and 2017.

3.3.3 Opioid specific vocabulary

Given the large user base of Reddit and the general tendency of the users in employing slang in the context of stigmatized behaviors, applying a query expansion procedure on Reddit is particularly helpful to gain information on how the topic is discussed. In particular, in our context, there is widespread use of slang and street names; therefore, our method is very helpful in acknowledging alternative names of drugs, like for instance, *sub* for *suboxone* and *bth* for *black tar heroin*.

As a byproduct of the methodology applied in Section 3.3.2 to find subspaces of discussion on opioids, by weighting each term of the vocabulary with Eq. Equation (3.3) we gain a topic-specific vocabulary. Opioid-related terms that are very topic-specific, i.e., with high probability in opioid-related subreddits and low probability in the whole corpus, have large positive values of $score(w \mid K)$. In contrast, stop-words and standard terms have small score values, as shown in Figure 3.2 (bottom). In this figure, we reported the top 2000 terms of the vocabulary ranked by their score$(w \mid K)$, plotted against their (ranked) probability of appearance in the corpus. As visible, most of the terms with high scores refer to opioid substances. A total of

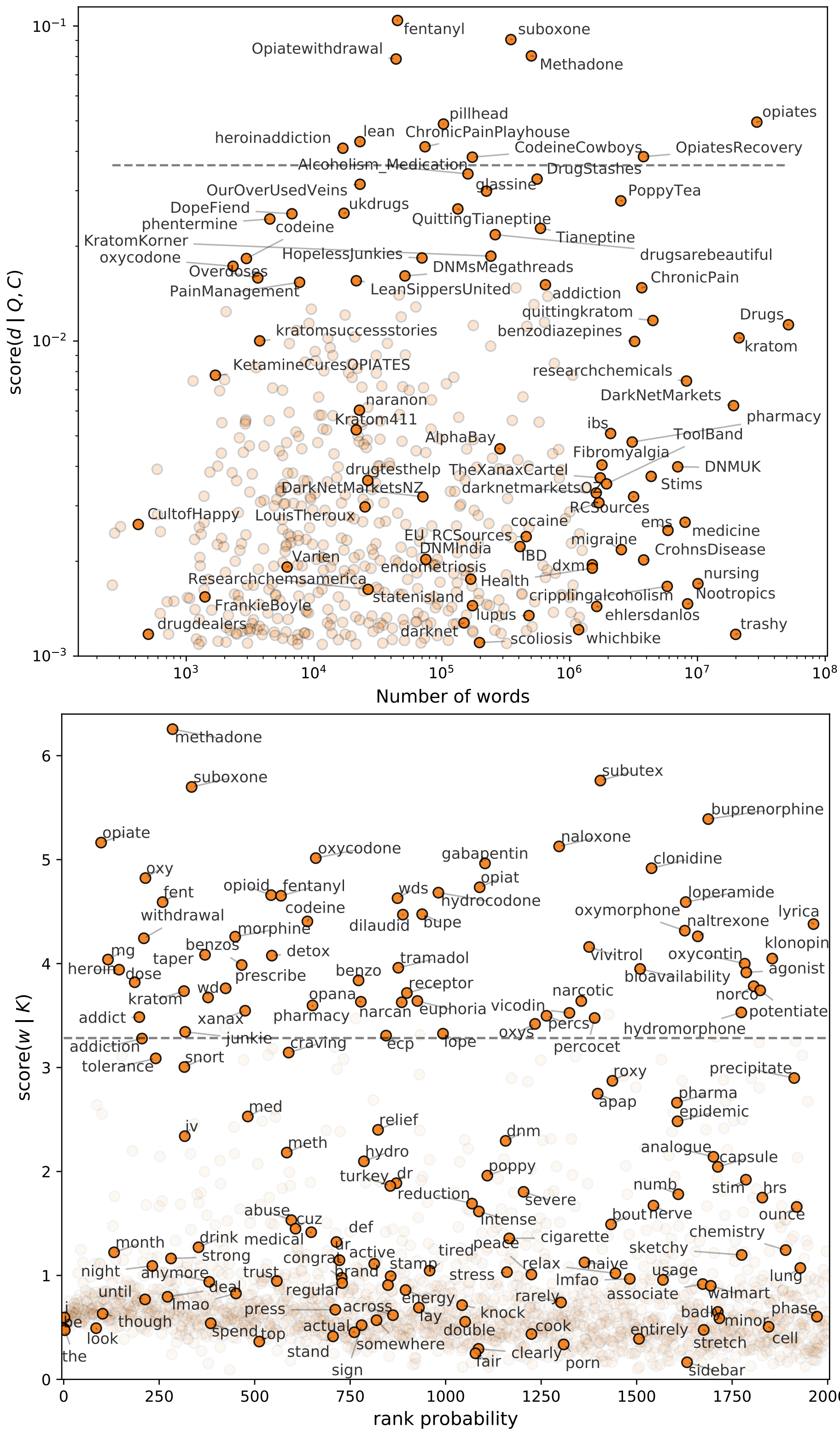


FIGURE 3.2: *Opiates subreddits* (top): individual subreddits are shown in a coordinate space of the number of words in the subreddit and the final ranking score. The subreddits above the dashed line are those selected as K opioids related subreddits. *Opiates vocabulary* (bottom): Top 2,000 terms sorted by rank probability of term in the set K. Terms above the dashed line were selected as query term candidates in the last step of the subreddit retrieval algorithm.

2616 terms out of the original 762,746 (0.3%) have a score higher than 1. The complete list of vocabulary terms ranked by score is available for research purposes [2].

3.4 Geolocating users on Reddit

To represent the interest-in-opioids in the US in a geospatial fashion, we need information about the geolocation of the users on Reddit. Unfortunately, Reddit does not provide any explicit information about users' location. Therefore in this section, we apply three different methodologies to infer a location for each user:

- *Self-reporting via regular expression.* Reddit users often disclose geographical information about themselves in submission or comment texts. We select all texts containing the expression `'I live in'`, for a total of 3,337,850 instances in 2016 and 2017, and we extract the words that follow as candidate locations. Next, we work to identify which candidates represent the US States and US cities. We start with a set of US cities from the GeoNames database [3] with a population higher than 20k, and we select only the candidate expressions that include both the city name and the State (e.g. 'Newark, California' or 'Newark, CA') to avoid confusion with cities with the same name (e.g. 'Newark, New Jersey'). Then we assign as candidate position the US State present these expressions. We continue with the same procedure applied to all US cities with a population higher than 200k, selecting expressions with the name of the city and their variants (e.g. "New York", "Big Apple"). After assigning the corresponding US State for these expressions and removing them from the candidates, we proceed by selecting the expressions with a State name (e.g., "Alabama", "California"). Among the initial set of candidate location expressions, we find 886,919 (27%) with an associated US State. By removing inconsistent self-reporting (13,374 users who reported more than one US State), we find the location of 378,898 distinct users.
- *Self-reporting via location flairs* In Reddit, *user flairs* are attributes that are attached to users' submissions or comments in a specific subreddit, usually selected by the users themselves. In some subreddits, the flairs are limited to a set of geographical locations (countries, states, cities, and city neighborhoods), meaning that users have the possibility to identify themselves with one of these locations. Therefore, we consider a user selecting a location flair equivalent to a user self-reporting its location. We scan for users participating in subreddits with location flairs referring to the US States, mapping them to their *flaired* positions by selecting the most common location flairs expressed. Using this approach, we locate 206,125 users to the 51 US States (including the District of Columbia).
- *Posting on location specific subreddits* Reddit includes subreddits which discuss topics specific to the culture and news of different geographical locations (e.g. `r/Alabama`, `r/Seattle` or `r/italy`). The subreddit `r/LocationReddits` keeps a curated list of these local subreddits. By crawling the page corresponding to North America [4], we collect the mappings of 2,844 subreddits to 51 US States. By assuming that a user who posts comments in one of these subreddits is likely to live in that location, we estimate the candidate position of 1,198,096 authors.

After retrieving US States candidate positions using the three methods above, we address the 12% of mapped users who expressed multiple locations. In order to uniquely map authors to the Us States, we assign each author a unique location as

[2] https://github.com/ISIFoundation/WWW19OpiatesAbuseSocialMedia
[3] http://www.geonames.org/
[4] https://www.reddit.com/r/LocationReddits/wiki/faq/northamerica

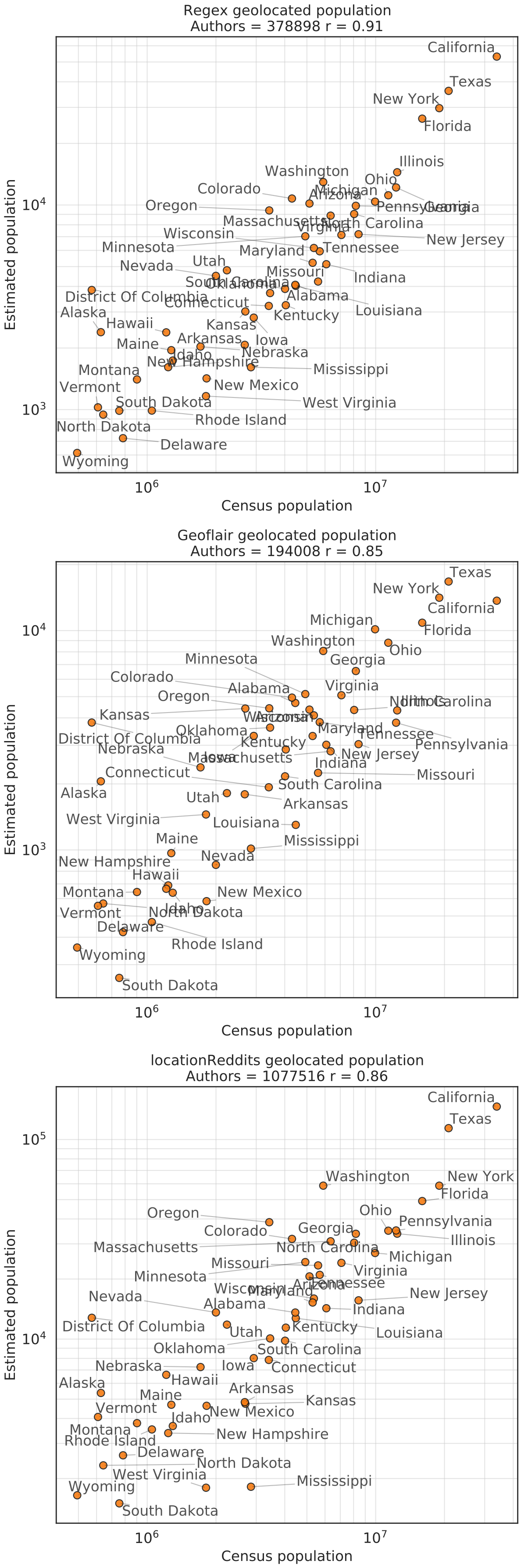


FIGURE 3.3: Scatter plot of the census population and the number of users geolocated via (top) regualrte expression (center) geoflairs and (bottom) LocationxReddits.

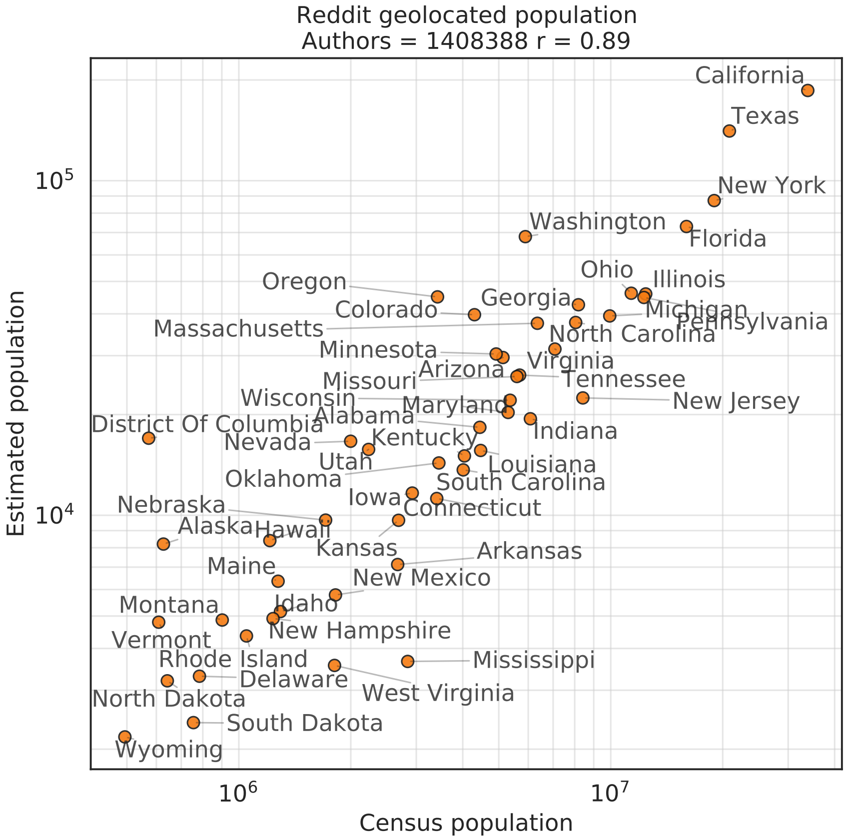


FIGURE 3.4: *Reddit geolocated population*: scatter plot of the number of geolocated Reddit users and census population.

the most frequent among the ones assigned by the author using the location flairs method and the LocationReddits method. We discard the authors whose most frequent location is not unique. This results in 194,008 authors retrieved via location flairs (5.9% loss) and 1,077,516 via LocationReddits (1.4% loss).

To make sure that the locations extracted have a correspondence with the actual population distribution in the United States, we evaluate the Pearson's r correlation between the logarithm of the *2000 US Census population* and the logarithm of the population assigned to the same US States using the three methodologies. The Results for all sources are in good agreement with the official statistics, showing a correlation of r= 0.85 for the positions extracted via Location flairs, r= 0.91 for those extracted via Regular expression, and r= 0.86 for the positions extracted via LocationReddits. All p-values are below $P \leq$ 10e-12. The subfigures in Figure 3.3 report the population of each State, retrieved with the three different methods and plotted against the Census Population.

Finally, in order to get a consistent signal, we merge the information from all three sources in a unique location indicator for each author. Some approaches have been proposed to geolocate users using language models (Han, Cook, and Baldwin, 2014). However, by considering only explicit geographical information directly provided by the authors, we rely on the following more conservative and possibly sounder approach to reduce misclassification. We consider the regular expression technique the most reliable due to its unambiguous self-reporting nature, resulting in the highest correlation with census data. We proceeded in the merging process by first assigning the authors their regular expression location, if present. If missing, we assign them their position from the joint information of location flairs and LocationReddits, extracted by summing the occurrences of locations expressed in the two sources and verifying the uniqueness of the most frequent location.

Using the above methodology, the complete set of geolocated users consists of 1,408,388 individuals. We measure a State representativeness in the order of 5.5 Reddit users per thousand US residents (median value among all US States). Although we acknowledge a potential bias due to heterogeneities in Reddit population coverage and users demographics, the number of Reddit users per State still holds a good linear correlation of $r = 0.89$ and p-value below $P \leq$1e-12 with the census population (Figure 3.4), making this proxy signal of population usable for estimates. Even though for some portions of the US territory, i.e. big cities or densely popalted counties, a finer granularity of geolocation could be reached and potentially used to discriminate between urban, suburban, and rural areas, in this work

3.5 Mapping the interest in opioid-related discussions

Conversations in opioid-related subreddits branch off in many topics, mainly regarding opioid usage, dosages, interactions with other substances, safe practices, and withdrawal, usually from a personal perspective. The authors of this subreddit, in general, share a common and firsthand interest in experiences tied to the use of opioids, communicating their health and addiction status and providing each other with personal experiences and support. Thus, the number of authors participating in the conversations in opioid-related subreddits (as identified in Section 3.3) is not to be considered as a crude number of opioid users and users with Opioid Use Disorder. Rather, it represents a proxy of users personally interested in the nonmedical use of opioids in the broadest sense.

Using the geographical information about the Reddit population estimated in Section 3.4 and having identified the authors interested-in-opioids in Section 3.3.2, we can estimate the geolocation of a part of the users interested in opioids. Out of the total digital cohort of users interested in opioids, we can geolocate 24% of users, corresponding to 9,026 individuals.

Finally, by computing the per-state fraction of geolocated users engaged in opioid-related subreddits over the total number of geolocated Reddit population, we can measure the *opioid-interest-prevalence* at the US State level. The resulting interest prevalence stands on average at 636 per 100,000 Reddit users across the US. In comparison, the CDC reports for 2016 an age-adjusted rate of overdose deaths of 19.8 per 100,000 population and an opioid prescription rate of 66.5 prescriptions dispensed per 100 persons. The green map in Figure 3.5 reports the per-state interest prevalence in opioids. Table 3.1 reports the aggregate number of authors interested-in-opioids, the total number of authors, and interest prevalence per 100,000 individuals for the regional divisions of the US. The area of greater interest according to our estimates is the South Region (Table 3.1). The region shows a high prevalence for Mississippi, Arkansas, Louisiana, and the highest measured value of 1,180 interested individuals per 100,000 population in West Virginia (Figure 3.5, green map). Middle Atlantic and New England States like Pennsylvania, New Jersey, and Rhode Island are also largely involved, showing high-interest rates ranging between 850 to 900 individuals per 100,000 population. In line with official statistics about drug overdose deaths, West and North Central States have the lowest interest rate also on Reddit, ranging from 341 per 100,000 in Nebraska to 510 per 100,000 in Minnesota.

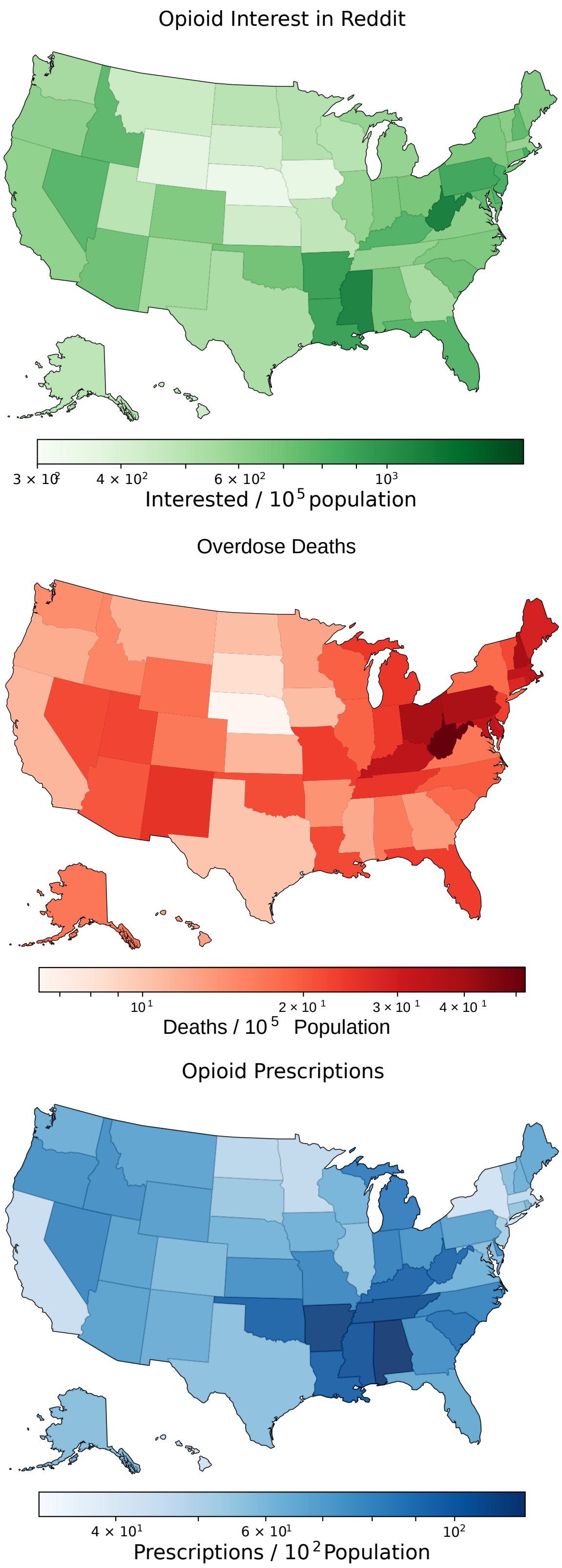


FIGURE 3.5: *US States distribution maps:* choropleth maps representing the overdose deaths rate for 2016 (red), the opioid prescription rate for 2016 (blue), the opioid interest rate in Reddit for 2016 and 2017 (green).

Region	Division	Opioids authors	Reddit authors	Interest prevalence
Northeast	Middle Atlantic	1,186	154,418	768.05
Northeast	New England	455	69,132	658.16
Midwest	East North Central	1,082	172,902	625.79
Midwest	West North Central	424	92,931	456.25
South	East South Central	457	63,269	722.31
South	South Atlantic	1,656	242,470	682.97
South	West South Central	1,079	177,856	606.67
West	Mountain	793	119,742	662.26
West	Pacific	1,894	315,668	599.10

TABLE 3.1: *Interest prevalence by US regional division*: number of opioids authors, total number of authors, and interest prevalence per 100,000 individuals measured on Reddit.

When comparing the estimated interest prevalence with the official statistics from the Centers for Disease Control and Prevention (Centers for Disease Control and Prevention (CDC), 2021) we can grasp different angles of the opioid crisis. In particular, we focus on opioid drug overdose deaths rates and retail opioid prescribing rates, both regarding 2016 (the most recent available dataset at the time of experimenting), shown in Figure 3.5 in red and blue, respectively. While encompassing two different aspects of the same underlying phenomenon, these two official statistics seem relatively uncorrelated and show a Pearson's correlation of $r = 0.068$ ($P = 0.637$). It is worth stressing that "gold-standard" data are the only sets of data provided by the CDC in 2017 that allow for comparisons between different States. In fact, although the counting of drugs overdose deaths includes every drug and is not broken down by drug type, the state-level estimates of opioid-related overdose deaths are affected by heterogeneities in the surveillance system and are not reliable.

The interest prevalence shows relatively high positive linear correlations with the counts estimated by the CDC, respectively showing a Pearson's correlation of $r = 0.45$ ($P = 8.4\text{e-}04$) with the opioid overdose deaths rate, and $r = 0.506$ ($P = 1.6\text{e-}04$) with the retail opioid prescribing rate. These correlations suggest that the proxy signal of interest-in-opioids measured on Reddit partially explains two observed phenomena that revolve around the opioid epidemic, measured by the standard public health surveillance systems. As a final check, we train a linear regression model to fit the estimated interest prevalence using the drug overdose death rates and the prescriptions rates as features. The signal predicted with this simple model, which accounts for both the prescription rates and the overdose deaths and predicted new values of interest prevalence, results in a higher correlation of $r = 0.655$ ($P = 1.7\text{e-}07$) with the estimated interest prevalence. This result confirms that the signal we measure on Reddit is potentially broader than the prescription rates and the opioid overdose deaths alone. Possibly, our measures are accounting for more complex aspects of the phenomenon, such as the nonmedical use of opioids that does not lead to an overdose death.

Leveraging the geolocated cohort, we can also evaluate the temporal variation of interest prevalence between 2016 and 2017 broken down by State. According to

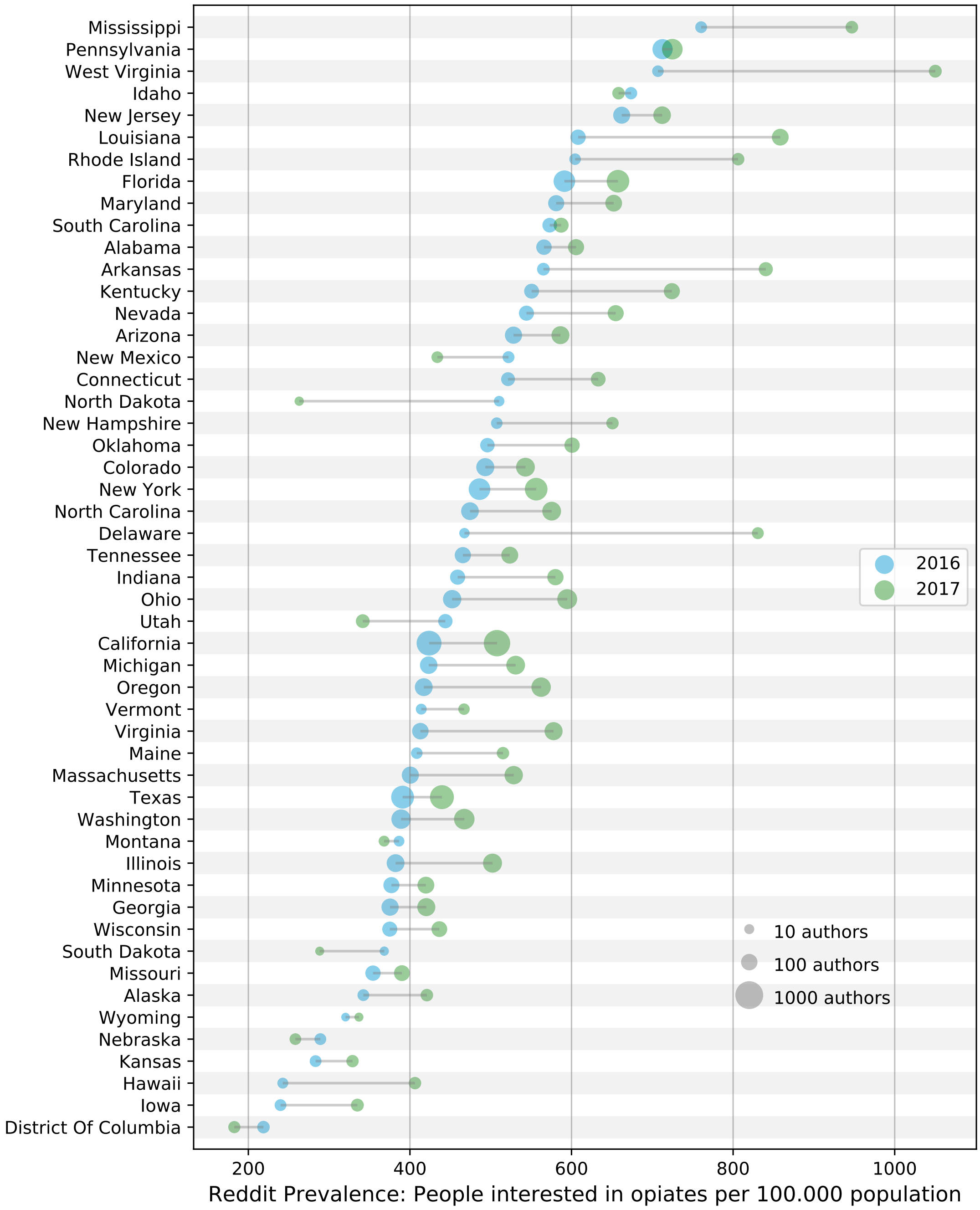


FIGURE 3.6: *Opioids interest prevalence:* number of Reddit authors per 100,000 Reddit population. Prevalence values for years 2016 and 2017 are reported on the x-axis. The size of the bubbles is proportional to the number of Reddit authors.

	Regular expression	LocationReddits	User flairs
Regular expression	-	0.76 (8.5e-11)	0.42 (2.2e-3)
LocationReddits		-	0.35 (1.3e-2)
User flairs			-

TABLE 3.2: Pearson's correlations (and p-values) between interest prevalence values evaluated separately for each geolocation method.

Figure 3.6, the interest prevalence decreased only in 8 States in that period. In general, we observe that in areas with good coverage of opioid-related users (namely, California, Texas, New York, Florida), the interest prevalence increased by 10% to 20%. It is worth stressing that no official data about 2017 drug overdose deaths and associated trends were available at the time of performing the experiments. Thus, our work highlights the tremendous potential of a digital epidemiology approach to gathering timely insights about hard-to-reach information on health-related topics at the population level.

A potential bias to our estimates might be due to heterogeneities in population coverage (see Figure 3.4), i.e., introduced both by the different Reddit penetration levels for different States and/or by the methodology applied to assign a location to users. Nevertheless, we expect that the effect of these biases is less apparent when calculating the interest prevalence from user-generated content since we assume that the same biases are present in the sampling of users who commented in opioid-related subreddits and in the sampling of users who did not.

Evaluating the prevalence of interest separately for each source, we observe in Table 3.2 some variations in prevalence correlation between sources with a general fair agreement, confirming that biases probably exist, but the overall signal is preserved. A different source of potential bias is relative to the identification of opioid-related subreddits. As a sensitivity analysis, we further investigate the effect of different subreddit selections. We evaluate the correlation of the interest prevalence between the ten subreddits identified in Section 3.3.2 and the interest prevalence evaluated with an increasing subset of those subreddits, ranked as outputted by the algorithm. As shown in Figure 3.7, even with a small subset of the selected subreddits, the estimated interest prevalence has a good agreement with the one measured with the entire set of subreddits.

3.6 Conclusions

With this work, we demonstrated that thanks to novel Information Retrieval techniques and text mining, it is possible to use digital data gathered on Reddit to conduct epidemiological surveillance and monitoring on social media. We designed a general-purpose Information Retrieval algorithm able to identify regions of interest on social media. Then, we applied it to gather the most relevant spaces of discussion related to firsthand opioid use on Reddit in 2016 and 2017. We believe that the algorithm we proposed, the set of opioid-related subreddits, and the domain-specific vocabulary of opioid-related terms we provided could be beneficial for new studies on Reddit regarding the opioid epidemics and other topics. Starting from almost 2 billion posts and over 74k distinct subreddits, in this work we selected a

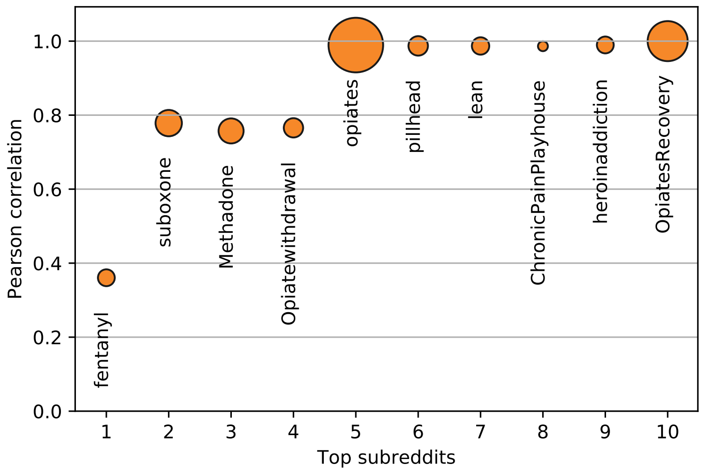


FIGURE 3.7: Pearson correlation between the prevalence according to the top 10 subreddits and the prevalence as calculated by taking only the top n subreddits with n going from 1 to 10. The size of the dot is proportional to the square root of the number of opioid related authors in the newly added subreddit (the biggest is `opiates` with 7,427 authors and the smallest is `ChronicPainPlayhouse` with 8 authors).

digital cohort of 37,009 users that show an explicit interest in the topic. We believe that this novel digital cohort might represent a valuable digital observatory on the opioid epidemic, which could be leveraged in future studies to study several social and health-related topics, such as pharmacovigilance and rehabilitation. Using three methods based on exploiting some characteristics proper of Reddit, we localized 1.5 million pseudonymous Reddit users at the US State level, with good agreement with census data. Finally, we provided an estimate of the interest in the consumption of opioids for each US State, and we highlighted the temporal variations of such interest from 2016 to 2017. The geographical heterogeneity of the synthetic signal of interest-in-opioids extracted with the presented approach partially encodes real-world signals from opioid prescribing rates and drug overdose deaths. The digital approach implemented in this work shows a complementary perspective to official public health surveillance, and we hope that competent health institutions might replicate our framework and procedures to perform continuous and timely public health monitoring.

Chapter 4

Understanding patterns of non-medical consumption

4.1 Scope

In this chapter, we aim to complement existing studies in the field of pharmacovigilance by using the content of firsthand conversations on Reddit to widen the current understanding on consumption patterns of opioids. The contributions in this chapter are manifold. First, we leverage and expand the Information Retrieval methodology proposed in Chapter 3 by identifying a large cohort of Reddit users showing explicit interest in firsthand opioid consumption, called *opioid firsthand users* or OFU in the following, spanning throughout five years from 2014 to 2019. Second, using word embeddings, we identify and catalog a large set of terms describing practices of nonmedical opioid consumption, making available to the research community the taxonomy of the Routes of Administration, the drug tampering methods, and their corresponding vocabularies. These terms are invaluable to performing exhaustive and at-scale analyses of user-generated content from social media. In fact, they include colloquialisms, slang, and nonmedical terminology established on digital platforms and hardly used in the medical literature. Third, we provide a longitudinal perspective on two essential pharmacovigilance aspects, showing the temporal evolution of the online popularity of opioids and quantitative characterization of the adoption of different ROA, with a focus on the less-studied yet emerging and relevant practices. Finally, we quantify the strength of association between ROA and drug-tampering methods to characterize its emerging practices. We investigate the interplay between these dimensions of pharmacovigilance, measuring odds ratios to shed light on the "how" and "what" facets of the opioid consumption phenomenon. To the best of our knowledge, our contributions are original in both breadth and depth, outlining a detailed picture of nonmedical practices and abusive behaviors of opioid consumption through the lenses of digital data.

While using a digital epidemiology approach has known advantages, extrapolating information from corpora of textual conversations, especially in social media, has to deal with the complexity of language usage. In particular, the language in online platforms usually counts among slang, contracted forms, and pictorial expressions like emojis, amongst the others. Moreover, linguistic modifications frequently occur in the discussion of taboo behaviors such as drug consumption (Allan and Burridge, 2006), underlining how the vocabulary of drug-related activities is rapidly evolving by nature. The extensive use of slang, street names, and non-usual/non-scientific terms to describe substances, consumption habits, and a wide variety of abuse-related behaviors (e.g., nonmedical use, addiction, recovery, routes of administration) represents a well-known issue to the law enforcement personnel (Drug Enforcement Agency (DEA), 2018). While the linguistic complexity of this topic on social media poses several methodological issues, it also carries opportunities, Drug-related slang embeds concepts and practices that are widespread in the user base but that are hard to capture through codified survey questionnaires, like the *recreational* and *nonmedical* use of opiates and opioid substances. In fact, most published statistics on nonmedical (mis)use of opioids often refer to a limited set of common prescription analgesics, overlooking both the emergence of misuse of other drugs and the incidence of illegal substances like heroin. Moreover, a better understanding of the opioids-related slang may be of primary importance to investigate polypharmacy trends. Due to the lack of a reference terminology (Peacock et al., 2019; Alho et al., 2020; Lovrecic et al., 2019), in fact, the widespread tendency in drug abuse to co-administer multiple substances is a phenomenon that is very difficult to quantify by means of official data sources. In addition to that, broader issues of taxonomy and terminology agreement have been raised within the scientific community (Savage et al., 2003), where terms to describe abusive behaviors and drug consumption are not always universally accepted by the scientific community and often lack uniformity, making interpretation and agreement difficult.

To decode the emerging slang of OFUs that is crucial for this study, we develop a procedure based on the use of well-established techniques of word embedding, *word2vec* (Mikolov et al., 2013) and *GloVe* (Pennington, Socher, and Manning, 2014). Algorithms of this type can learn complex non-linear relationships among terms within a corpus and have proven valid in deepening the context understanding in digital epidemiology studies. For instance, the compact high-dimensional representation of terms provided by word embeddings has been used to uncover unknown drug slang terms (Simpson et al., 2018), to investigate transitions into drug addiction (Lu et al., 2019), and as a semantic feature in discovering alternative treatments for opioid use recovery (Chancellor et al., 2019b). In this work, we leverage these techniques to expand the current vocabulary knowledge on some aspects of the nonmedical use of opioids in light of slang on social media.

As discussed in Chapter 2 most of the research works that estimate the prevalence of adoption of opioid substances and routes of administrations for nonmedical opioid use neglect less common substances. These studies usually overlook less diffused ROA, such as rectal, transdermal, and subcutaneous administration. Moreover, while acknowledging drug tampering as an essential constituent of drug abuse, these studies never or rarely quantify its importance and effects at large-scale. Hence, in this chapter we estimate substance adoption of opioids for nonmedical use, considering both prescription opioids and common illicit opiate substances, expanding previous work by showing their temporal evolution over several years. Our work also extends the current literature by providing new terminology related to ROA and Drug tampering methods and measuring the adoption of less studied yet relevant emerging ROA in the context of nonmedical use of opioids. Moreover, our work is one of the first quantitative attempts at measuring the interplay between nonmedical drug use and drug tampering, portraying a very detailed picture of opioid use and abuse.

4.2 Data preparation

In this chapter, we utilize the textual part of the submissions and the comments collected on Reddit from 2014 to 2018. We pre-process each year separately, filtering out the subreddits with less than 100 comments in a year. We use the spaCy (SpaCy, 2020) package to remove English stop-words, inflectional endings, and tokens with less than 100 yearly appearances. We adopt a bag-of-words model for populating a set of vocabularies of lemmas, one for each year of the dataset. The sizes of the obtained Vocabularies range from 300,000 to 700,000 lemmas, with a size growth of approximately 30% new lemmas each year. In Table 4.1, the number of unique comments and unique active users per year is reported. The volume of conversations and the active user base show a steady growth of approximately 30% per year. This dataset's distribution of posts per user shows a heavy tail: similar to the activity of users on other social media platforms (Barabasi, 2005; Malmgren et al., 2009; Muchnik et al., 2013), the majority of users publish few comments, and the remaining minority of core users and subreddit moderators produces a large portion of the content. Moreover, a nonnegligible percentage of posts, respectively 25%, and 7%, of submissions and comments, are produced by authors who deleted their usernames.

All the analyses we perform in this chapter are done on a subset of subreddits focused on opioid consumption, which are identified using the procedure described in Section 4.3. For the sake of brevity, we restrict the analyses of odds ratios, shown in Section 4.6, to comments and submissions created during 2018.

Year	Reddit comments	Reddit authors	Opioid subreddits	Opioid comments	Opioid authors	Authors' prevalence
2014	545,720,071	8,149,234	19	386,984	12,381	0.0015
2015	699,245,245	10,673,990	19	470,609	15,888	0.0015
2016	840,575,089	12,849,603	25	612,619	21,791	0.0017
2017	1,045,425,499	14,219,062	30	866,023	28,358	0.0020
2018	1,307,123,219	18,158,464	25	919,036	33,700	0.0019

TABLE 4.1: Dataset Statistics.

4.3 Identification of firsthand opioid consumption on Reddit

We leverage the semiautomatic information retrieval algorithm presented in Chapter 1 to identify relevant subreddits for each year on the topic of interest. As previously discussed, this approach aims at retrieving topic-specific documents by expressing a set of initial keywords of interest. Here, we identify a set of subreddits S_y ranked by relevance for each year via an iterative query expansion process, also retaining a list of relevant terms Q_y. We merge all the query terms in a set $\bar{Q} = \bigcup_y Q_y$ containing 67 terms. To ensure that the sets S_y of subreddits selected by the algorithm each year are effectively referring to the opioid-related topics, and in particular to nonmedical opioid consumption, we perform a manual inspection on the union of the top 150 subreddits for each year, for a total of 554 unique subreddits. Three independent annotators, including a domain expert specialized in anti-doping analyses, inspect a random sample of 30 posts, checking for subreddits (1), mainly focused on discussing the use of opioids, (2) mainly focused on firsthand usage, and (3), not focused on medical treatments. These checks yield a total of 32 selected subreddits, with a Fleiss' k inter-rater agreement of $k = 0.731$, which suggests a substantial agreement, according to (Landis and Koch, 1977). Table 4.2 presents the complete list of the subreddits selected, broken down by year. Automatic language detection performed comparatively with langdetect (langdetect, 2020), cld2 (pycld2, 2020), and cld3 (pycld3, 2020), shows that about 90% of posts of the selected subreddits are expressed in English and approximately 5% in non-English languages. The rest of the posts are too short or full of jargon and emojis to detect any language algorithmically.

Assuming that an author who writes in one of the selected subreddits is personally interested in the topic, we identify a cohort of 86,445 unique opioid firsthand users involved in direct discussions of opioid usage across the period of study. Summary statistics are reported in Table 4.5: for each year, we compute the number of unique active users and the volume of comments shared, as well as the user's relative prevalence over the entire amount of Reddit activity. We observe growth in the number of active users from 2014 to 2017, with 15 to 19 users interested in opioid consumption out of every 100,000 Reddit users.

4.4 Vocabulary expansion

4.4.1 Methodology

The methodology to extend the vocabulary on opioid-related domains with user-generated slang and colloquial forms is implemented in two steps. First, we train a word-embedding model (word2vec (Mikolov et al., 2013)) on all the comments and submissions in our dataset of opioid-related-subreddit. Relevant training parameters are displayed in Table 4.3. The algorithm learns the language model and the semantic relationships in the corpus and maps the terms in the vocabulary to vectors in a latent vectorial space, the embedding space.

Second, starting from a set of seed terms K (e.g., a list of known opioid substances), we expand the vocabulary by navigating the semantic neighborhood $E^n_w = neighbours(w, n)$ of each element $w \in \bar{Q}$ in the embedded space. We consider the $n = 20$ semantically closest elements in terms of cosine similarity for our task. Then, we merge the terms of the neighborhood of each seed term in a candidate expansion set $\bar{E} = \bigcup_w E^n_w$, together with the seed terms K if not already included. Finally, relying on the knowledge of a clinical and forensic toxicologist, we manually select and categorize the relevant neighboring terms, obtaining an extended vocabulary V. To understand the most unusual terms, we also rely on the help of search engine queries and a crowdsourced online dictionary for slang words and phrases (Urban Dictionary (Urban Dictionary, 2020)).

Figure 4.1 shows an example of the vocabulary expansion procedure, in which the high-dimensional vectors representing the terms in the embedding are projected to two dimensions using the Uniform Manifold Approximation and Projection (UMAP) algorithm (McInnes et al., 2018). As visible from the figure, terms with similar meaning or semantically close appear close in the embedding space.

As a sensitivity analysis, we train with the same procedure an alternative embedding model, namely GloVe (Pennington, Socher, and Manning, 2014)), and we compare the effectiveness of our trained models for topical coherence. In the case of vocabulary expansion of opioid substance terms, that is, using $K = \bar{Q}$ as seeds, the two models capture 100 terms in common out of their respective candidate terms. However, the word2vec model shows a higher number and a larger percentage of

Subreddits	2014	2015	2016	2017	2018
opiates	x	x	x	x	x
OpiatesRecovery	x	x	x	x	x
lean	x	x	x	x	x
heroin	x			x	x
suboxone	x	x	x	x	x
PoppyTea	x	x	x	x	x
Methadone	x	x	x	x	x
Opiatewithdrawal	x	x	x	x	x
fentanyl		x	x	x	x
codeine	x	x	x	x	x
HeroinHeroines					x
heroinaddiction		x	x	x	x
oxycodone	x	x	x	x	x
opiatescirclejerk	x	x	x	x	x
loperamide			x	x	x
Opiate_Withdrawal				x	x
OpiateAddiction			x	x	x
PoppyTeaUniversity				x	x
random_acts_of_heroin	x	x	x	x	x
Norco			x	x	x
GetClean				x	x
0piates	x	x	x	x	x
zubsolv	x			x	x
oxycontin	x	x	x		
CodeineCowboys		x	x	x	
OurOverUsedVeins	x	x	x	x	x
LeanSippersUnited				x	
HopelessJunkies			x	x	
KetamineCuresOPIATES				x	
AnarchyECP	x		x	x	
PSTea			x		
glassine	x	x	x	x	

TABLE 4.2: Subreddits discussing firsthand nonmedical use of opioids. An X marks the presence of a subreddit in a specific year.

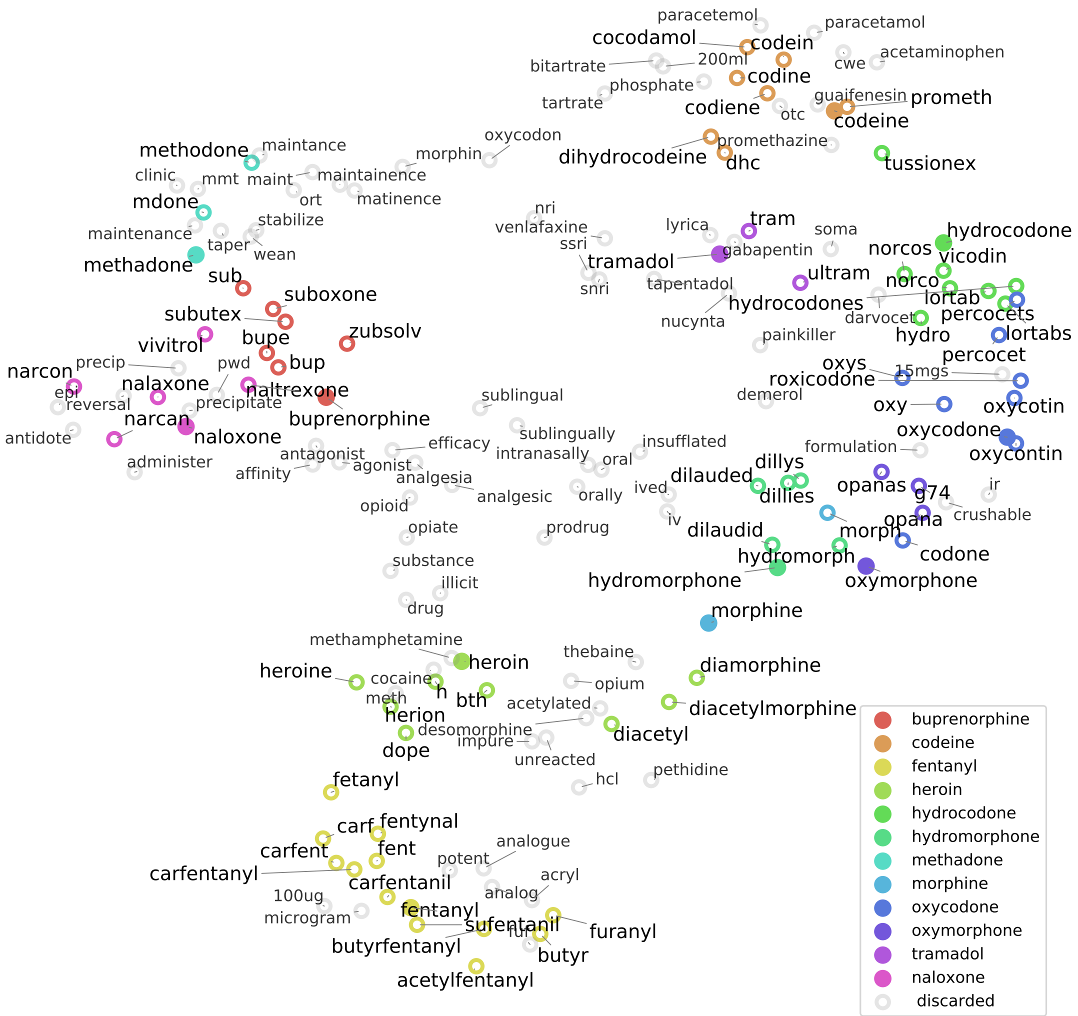


FIGURE 4.1: Two-dimensional projection of the word2vec embedding, modeling the semantic relationships among terms in the Reddit opioids data set. Filled markers represent the seed terms K. Expansion terms, represented with hollow markers, are colored according to their respective initial term if accepted or in gray if discarded. The nature of the relationships between neighboring terms varies, representing (1) equivalence (e.g., synonyms), (2) common practices (e.g., the use of methadone for addiction maintenance), or (3) co-use (e.g., the cluster of heroin, cocaine, and methamphetamine).

accepted terms (Table 4.4). Moreover, the volume of comments that include an accepted term is almost double if using the vocabulary of word2vec rather than the vocabulary of GloVe. Hence, we choose word2vec as the reference word-embedding model for our task.

4.4.2 Opioid substances, Routes of administration, and Drug tampering methods

We apply the vocabulary expansion methodology to extract and expand domain-specific vocabularies and to characterize the temporal unfolding of interest (see Section 4.5) in different opioid substances, routes of administration, and drug-tampering

	Min term count	Vector size	Context window	Negative Sampling	Training Epochs
word2vec	5	256	5	10	200
GloVe	5	256	10	-	300

TABLE 4.3: Relevant training parameters of the word embeddings. All the other parameters are set to default values. Two state-of-the-art word embedding models, namely word2vec, and GloVe, have been trained with all the comments and submissions in our subreddits dataset. After a-posteriori validation by a domain expert in terms of topical coherence, we choose word2vec as the reference word embedding model.

	Candidate terms, n	Accepted terms, n (%)	Comments[a], n
word2vec	297	128 (43.1)	225165
GloVe	369	110 (29.8)	144564

TABLE 4.4: Comparison of term expansions of opioid substances for the 2 trained models. [a]Comments in the corpus mentioning at least one term of the respective accepted terms for vocabulary expansion.

methodologies. We start from a review of the relevant medical research, and we collect an initial set of terms referring to the most common opioid substances, ROA (McCabe et al., 2007; Butler et al., 2011; Kirsh, Peppin, and Coleman, 2012; Young, Havens, and Leukefeld, 2010; Coon et al., 2005; Rivers Allen and Bridge, 2017; Mastropietro and Omidian, 2014; Hart et al., 2014; Surratt et al., 2017), and drug-tampering methods (Mastropietro and Omidian, 2014; Hart et al., 2014).

Then, starting with the opioid substances, we expand the original sets of terms with neighboring terms in the embedding. The outputs of the algorithm are reviewed by a domain expert and organized in coherent classes corresponding to known opioids and opiates. The resulting vocabulary of opioid substances is shown in Table 4.5. It is worth noting that the vocabulary expansion procedure considerably increases the richness of the terminology related to the domain of interest and, consequently, the volume of conversations on Reddit that contain these terms. For example, for the *heroin* category, we observe a 62% growth in the relevant conversations retrieved containing terms equivalent to *heroin*, compared to the documents containing only the original term *heroin* (Table 4.5).

Then, we proceed by searching for alternative terms about the routes of administration. The enriched vocabulary for ROA, after quality check with the domain expert, is further organized in a 2-level hierarchical structure consisting of Primary ROA and Secondary ROA, reported in Table 4.6. This taxonomy does not have a strict medical interpretation, nor is it intended to be a comprehensive review of all possible ROA. However, this structure can give order to otherwise unstructured collections of words and help interpret the results by letting the researcher dig deeper into specific sub-categories of ROA.

Finally, we extract and organize the vocabulary related to drug-tampering techniques, as shown in Table 4.7. We consider the act of chewing pills a second-level route of administration under the *ingestion* category (Katz et al., 2008; Kirsh, Peppin, and Coleman, 2012; Gasior, Bond, and Malamut, 2016) instead of considering it a

Substance	Terms	$\Delta Volume, \%$
Heroin	**bth**, diacetylmorphine, diamorphine, dope, **ecp**, goofball, goofballs, gunpowder, h, **herion**, **heroin**, heroine, heron, smack, speedball, speedballing, **speedballs**, tar	62
Buprenorphine	bup, **bupe**, **buprenorphine**, **butrans**, sub, **suboxone**, **subutex**, zub, **zubsolv**	61
Hydrocodone	hydro, **hydrocodone**, **hydrocodones**, **lortab**, **lortabs**, **norco**, **norcos**, tuss, **tussionex**, vic, vicoden, **vicodin**, **vicodins**, **vicoprofen**, **vics**, vikes, viks, **zohydro**	38
Codeine	cocodamol, **codein**, **codeine**, **codiene**, codine, dhc, **dihydrocodeine**, prometh, sizzurp, syrup	28
Oxymorphone	g74, **opana**, opanas, **oxymorphone**, panda	25
Tramadol	desmethyltramadol, dsmt, tram, **tramadol**,**ultram**	22
Hydromorphone	dil, dilauded, **dilaudid**, dilaudids, **dillies**, dilly, dillys, **diluadid**, **hydromorph**, **hydromorphone**	21
Oxycodone	15s, 30s, codone, contin, ms, oc, ocs, **oxy**, **oxycodone**, **oxycontin**, oxycontins, **oxycotin**, **oxys**, **perc**, **percocet**, **percocets**, percoset, percosets, **percs**, perk, **roxi**, **roxicodone**, **roxie**, **roxies**, **roxis**, **roxy**, **roxycodone**, **roxys**	14
Morphine	kadian, morph, **morphine**	5
Fentanyl	**acetylfentanyl**, butyr, butyrfentanyl, carf, carfent, **carfentanil**, carfentanyl,**duragesic**, **fent**, **fentanyl**, fents, fentynal, fetanyl, furanyl, sufentanil, u47700	4
Antagonist	**nalaxone**, **naloxone**, naltrexone, **narcan**, narcon, revia, viv, **vivitrol**	1
Methadone	mdone, **methadone**, **methodone**	1

TABLE 4.5: Vocabulary of opioid substances. Starting from a candidate expansion set $\bar{E}$, comprising 297 unique terms, the final expansion terms considered equivalent to a substance were gathered in the same class. Terms in $\bar{Q}$ are highlighted in bold. The increase in the volume of occurrences of a substance using the terms in the expanded vocabulary compared with only using the terms in $\bar{Q}$.

drug-tampering method, as some research might suggest (Mastropietro and Omidian, 2014).

By observing the vocabularies in Tables 4.5,4.6,4.7 resulting from the expansion algorithm, we can ascertain the importance of enriching domain expertise with user-generated content. We observe that some shared features are captured across categories. Our method is able to detect synonyms and common short names, very specific acronyms (e.g., "cwe" for cold water extraction (Bausch et al., 2012)), slang expressions like "sippin", often used when referring to the act of drinking codeine mixtures (Hart et al., 2014), nicknames (e.g., "panda" for oxymorphone), and polypharmacy instances (e.g., "speedball" and "goofball" (Ellis, Kasper, and Cicero, 2018)). The vocabulary expansion underlines the habit of naming prescription dosages, usually stamped on the tablets, in place of the commercial names of the substances (e.g., "30s" for oxycodone). Moreover, from some terms found in the expansion procedure, we can deduce that OFU discuss variants of the substances (e.g., "bth" and "ecp" for *black tar heroin* and *East Coast powder*), research chemical equivalents (e.g., "u47700" equivalent of fentanyl (Prekupec, Mansky, and Baumann, 2017)), and formulations intended for veterinary use (e.g., sufentanil, carfentanil).

Primary ROA	Secondary ROA	Terms
Ingestion	Oral	bolus, buccal, gulp, mouth, mouthful, **oral**, orally, **swallow**
	Sublingual	**sublingual**, sublingually, tongue, tounge
	Drink	chug, drink, pour, pourin, **sip**, sipper, sippin, swig, swish
	Chew	**chew**, chewy, chomp, gum
	General Ingestion	**ingest**, ingestion
Inhalation	Intranasal	intranasal, intranasally, nasal, nasally, nose, nostril, rail, **sniff**, sniffer, sniffin, snoot, snooter, **snort**, snorter, tooter
	General Inhalation	breath, breathe,dab, exhale, inhalation, **inhale**, insufflate, insufflated, insufflating, insufflation, puff, toke, tokes, vap, vape, vaped, vapes, vaping, vapor, vaporise, vaporize, vaporizer, vapour
	Smoking	bong, fume, hookah, pipe, **smoke**, smoker, smokin, spliff
Injection	Intramuscular	deltoid, imed, iming, **intramuscular**, intramuscularly
	Subcutaneous	**subcutaneous**, subcutaneously, subq
	Intravenous	arterial, bloodstream, **intravenous**, intravenously, **iv**, ivd, ived, iving, ivs, vein, venous
	General Injection	bang, **inject**, injectable, injection, parenteral, shoot, shot
Rectally	Rectally	anal, anally, **boof**, boofed, boofing, bunghole, butt, pooper, **rectal**, rectally
Other ROA	Dermal	cutaneous, dermis, **transdermal**, transdermally
	Urogenital	vaginal
	Intrathecal	intrathecal

TABLE 4.6: Taxonomy defining the ROA categories and their corresponding terms. Primary ROA include all the expansion terms considered for the appropriate secondary ROA (original candidate expansion set comprised 199 unique terms). Seeds in *K* are highlighted in bold.

Transformation	Terms
Brew	**brew**, brewer, **homebrew**
Concentrate	**concentrate**, concentrate,concentration, purify
Dissolve	desolve, dilute, disolve, disolved, disolves, **dissolve**, solute, solution, soluble, soluable,
Evaporate	evap, evaporate
Extract	**cwe**, **extract**, extraction
Grind	chop, **crush**, crushable, crusher, **grind**, grinded, grinder, ground, pulverize
Heat	boil, **heat**, melt, microwave, overheat, simmer
Infusion	infuse, **infusion**, tea, tincture
Peel	peal, peel, shave
Soak	**soak**, submerge
Wash	rewash, rinse, **wash**

TABLE 4.7: Vocabulary of drug-tampering methods. Expansion terms referring to the same drug-tampering method are grouped in the corresponding transformation classes (original candidate expansion set comprised 179 unique terms). Seed terms *K* are highlighted in bold.

The vocabulary of ROA includes and categorizes both medical terms, adding terms scarcely considered in previous studies like "vaping" and nonmedical or unconventional administration terms, such as "chewing," "snorting," "smoking," and "boofing" (Rivers Allen and Bridge, 2017). Our taxonomy also enables to disambiguate common primary ROA, such as *injection* and *ingestion*, into specific secondary ones, like *subcutaneous* (Rivers Allen and Bridge, 2017) and *sublingual* administrations.

Finally, the drug-tampering vocabulary captures tampering methods that modify the physical status of the substances, like crushing and peeling, and some that alter the chemical characteristics of the substances, like dissolving, washing, and heating (Mastropietro and Omidian, 2014). We believe that even if this vocabulary might not be exhaustive of all drug-tampering methods, it offers a novel evidence-based perspective on the topic compared with the existing literature. The expanded vocabularies prove essential to fully incorporating the language complexity of online discussions and taboo behaviors (Allan and Burridge, 2006) into at-scale analyses. Hopefully, our contribution might be helpful in the future to find and understand new abusive behaviors that are discussed online, ultimately driving future research to yield more effective prevention methods.

4.5 Popularity of opioid substances and ROA

In order to have a cross-sectional view of the habit of consumption of opioids, we investigate the temporal unfolding of the popularity of the opioid substances and routes of administration.

We measure the popularity of substances and ROA as the fraction of authors mentioning a substance or ROA in each trimester from 2014 to 2018 over the number of OFU active in the respective periods, in order to account for the natural growth of the user base in Reddit. Naturally, we consider as valid mentions for a said substance or ROA all the respective equivalent terms gathered via vocabulary expansion. To discount potential biases due to users with high activity, we binarize the mentioning behavior at the user level. In this work, we provide a relative measure of popularity and not the raw count of authors mentioning the substances/ROA to account for the constantly increasing volume of active users on Reddit.

Figure 4.2 shows the evolution of the popularity of opioid substances, revealing a decrease in the usage of heroin and a rise in fentanyl and codeine. Figure 4.3 shows the estimated temporal evolution of the relative popularity of the routes of administration, measured in quarterly snapshots. The subfigures group the ROA divided by Primary ROA, i.e., Injection, Inhalation, Ingestion, Rectal administration, and Other, marked by thicker lines. Thinner lines mark secondary ROA.

With the assumption that the share of users mentioning a term related to opioid use is a proxy of firsthand involvement in opioid-related activities, the cross-sectional views in Figure 4.2 and Figure 4.3 can be used to rank the popularity of nonmedical usage of opioid substances and ROA, and their adoption trends.

Ranking the substances by average share, we can see that heroin is by far the most widespread substance, mentioned on average by one in every three users. Its share of users, though, is steadily decreasing, with a loss of 10% in agreement with results reported in state-specific findings by Rosenblum, Unick, and Ciccarone (2020). Buprenorphine and oxycodone are the most mentioned prescription opioids; while they show a reasonably static behavior in time, the relative importance of hydrocodone decreases (Black et al., 2020), possibly due to more stringent prescription

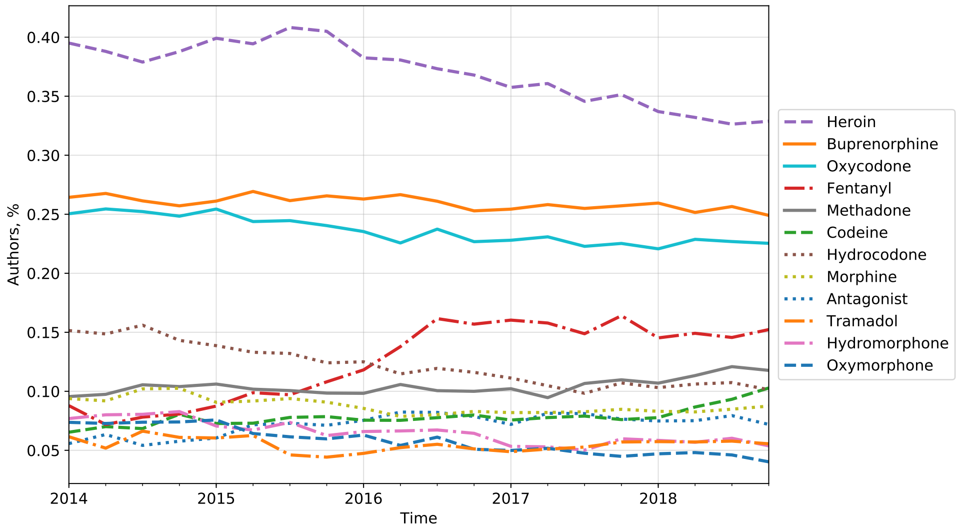


FIGURE 4.2: Popularity of opioid substances among opioid firsthand users on Reddit. Each line represents the share of opioid firsthand users mentioning an opioid substance, measured quarterly from 2014 to 2018.

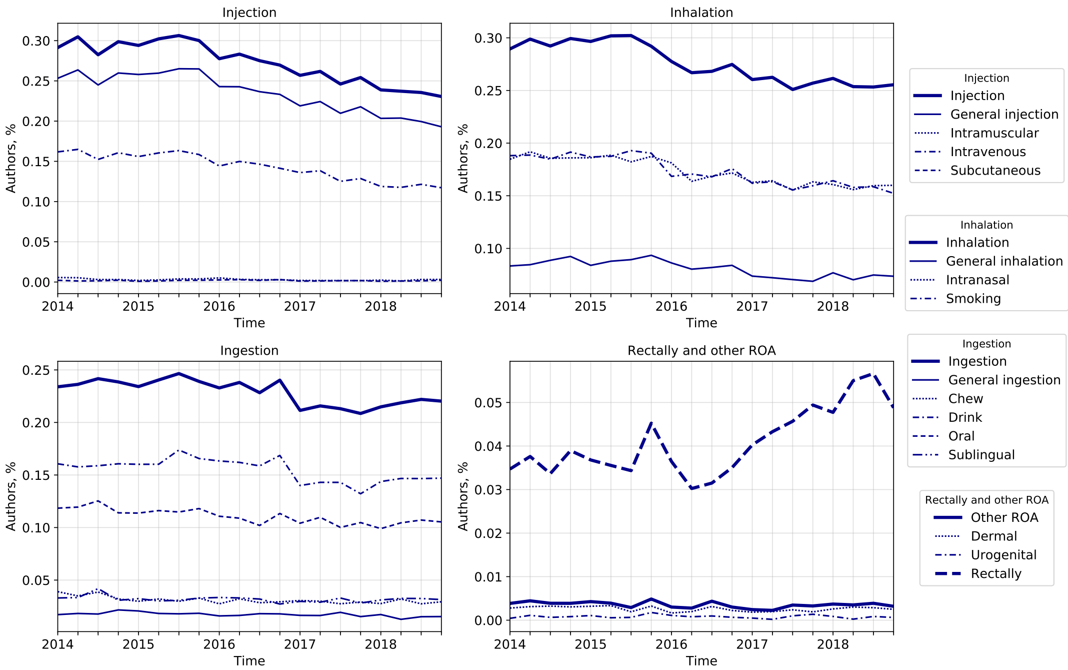


FIGURE 4.3: popularity of routes of administration among opioid firsthand users on Reddit. Each line represents the fraction of opioid firsthand users mentioning a ROA-related term, measured quarterly from 2014 to 2018. Thick lines represent the share of authors mentioning primary ROA, evaluated by aggregating the contributions of all the corresponding secondary ROA.

regulation starting in 2014 (Drug Enforcement Administration (DEA), 2014). In contrast, we do not find evidence of drastic changes in oxymorphone adoption after its partial ban in 2017 (Food and Drug Administration, 2017). The evolution of fentanyl shows the most abrupt behavior, dramatically increasing in popularity since 2016.

The volume of mentions to this substance in 2018 increased by almost 1.5 times compared with 2014, confirming fentanyl and its research chemical equivalents as one of the current threats (Ciccarone, 2019; Black et al., 2020) in the panorama of opioid substances.

ROA adoption is led by injection and inhalation, the most popular ROA across the years, mentioned by one of every three authors at their peak. These primary administrations are followed closely by ingestion. On average, rectal use and other ROA involve a significantly lower share of users of around 5% and less than 1%, respectively. Nevertheless, rectal administration shows a sharp relative increase in popularity since 2016, almost doubling its share and signaling a new potential emerging trend. The administration through inhalation is equally staggered by two secondary ROA, intranasal and smoking. This is a strong indicator that this route of administration is indeed capturing the nonmedical use of opioids.

These results show in a data-drive way which substances are currently gaining popularity and may give prevention programs a strategic advantage, especially if consumption trends can be localized geographically (Balsamo, Bajardi, and Panisson, 2019; Basak et al., 2019; Schifanella et al., 2020), enabling to focus on the interventions needed to prevent early adoption of emerging dangerous substances like fentanyl. Moreover, tracking the evolution of interest in prescription opioids might help evaluate the efficacy of ban policies, as in the case of oxymorphone. Understanding which ROA are the most adopted might eventually help address targeted campaigns to inform the users on safer practices, develop better tamper-resistant prescription drugs, and ultimately inform the health system of the health risks specific to opioid adoption.

4.6 Measuring strength of associations of non-medical opioid use

In this section, we shed light on the interplay between the "how" and the "what" dimensions of opioid consumption, focusing on characterizing the complex patterns of nonmedical consumption of opioids that involve drug tampering and nonmedical routes of administration.

We evaluate the odds ratios (ORs) based on co-mentions of terms to quantify the pairwise strength of the association between substance use and ROA, substance use and drug-tampering methods, and ROA and drug-tampering methods. We count the posts in our corpus containing a reference to terms in each of these three categories under the assumption that the co-mention of terms related to two of these categories, e.g., a substance to its ROA or drug-tampering method, is a proxy of association of the two. Based on these counts, we evaluate contingency tables and odds ratios. The odds ratios, significance, and confidence intervals are estimated using chi-square tests implemented in the statsmodel Python package (Seabold and Perktold, 2010). We set the significance level to $\alpha = 0.01$.

The number of sentences in Reddit posts varies greatly, but the posts are generally relatively short; approximately 50% of them have two sentences or less, as seen in Figure 4.4. However, as about 20% of posts have more than ten sentences, one should be cautious in adopting a bag-of-words approach to measure co-occurring terms. Hence, as a sensitivity analysis, we assess the effect of the proximity of terms on the characterization of odds ratios in terms of "sentence distance". First, we modify the definition of co-occurrence, introducing a distance threshold ρ at the sentence level. Then, we explore the range of distances $\rho \in \{0, ..., 5\}$, where $\rho = 0$ indicates

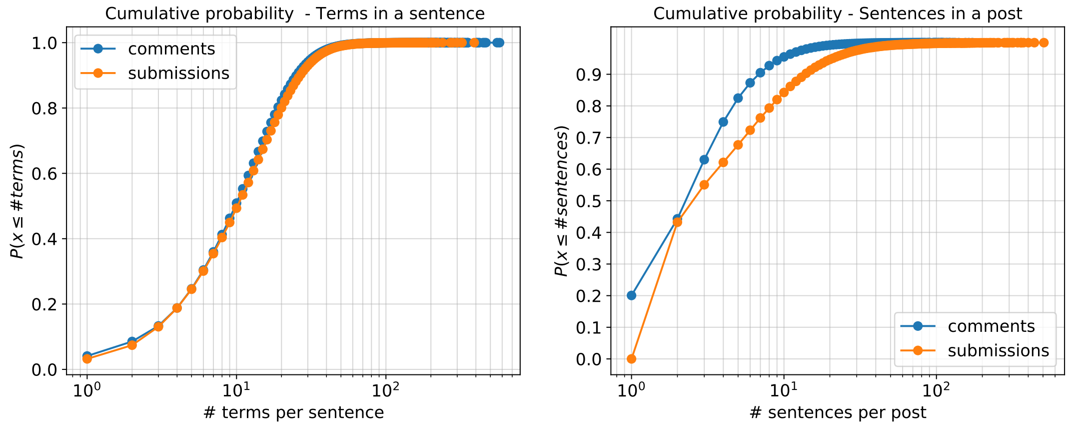


FIGURE 4.4: Cumulative probability of finding n or fewer terms in a sentence for submissions and comments (left panel). Cumulative probability of having n or fewer sentences in a submission or a comment (right panel). Plots refer to the selected subreddit in 2018.

that co-occurrence appears within the same sentence, and $\rho > 0$ measures the distance in both directions (e.g., $\rho = 1$ includes the first preceding and consecutive sentences). The value $\rho = \infty$ indicates the scenario in which we consider the entire post as a reference. Accordingly, given a threshold ρ in the construction of the contingency table, the co-occurrence event between two terms is conditioned to their distance being less than or equal to ρ. Conversely, we consider the terms of two categories as separate events in cases of distance above the threshold. To limit the chance of including spurious correlations due to the co-occurrences of terms far apart in the posts, we conservatively select $\rho = 1$, (i.e., considering only the co-occurrence of terms within a sentence or in the first adjacent sentences) for computing the ORs.

It is essential to consider that the OR measures do not imply any form of causation but rather surface correlations used in hypothesis formation. To better interpret the results of this analysis, in some cases, manual inspection of the comments mentioning the variables under investigation is performed following the directives on privacy and ethics (see Section 2.5).

Figure 4.5 shows in blue the results of the OR analysis at $\rho = 1$, for four of the most widespread substances (i.e., heroin, buprenorphine, oxycodone, and fentanyl) with the secondary ROA (upper panel) and the drug-tampering techniques (lower panel). Figure 4.6 shows the odds ratios of primary ROA and drug-tampering methods. For reference, the green markers in the figures represent the ORs obtained at $\rho = 0$ and $\rho = \infty$ for the same categories. In the plots, the horizontal lines indicate the value and the 95% confidence intervals of the ORs, while the radius of the circles centered on the ORs is proportional to the sample of co-mentions. The associations that are not statistically significant (P>.01) are reported in gray. The dashed vertical line corresponds to an OR of 1, for reference. Figure 4.7,Figure 4.8 and Figure 4.9 positioned at the end of the chapter), provide the complete set of results for all the substances identified and the secondary ROA. Due to the low representativeness of intrathecal and urogenital ROA with most of the tampering-related terms, we omit those categories from the analysis.

By jointly considering the results of the odds ratios , we can outline complex preferences for the nonmedical use of opioids, triangulating substance use, ROA, and drug-tampering methods. We notice that most substances exhibit more than one

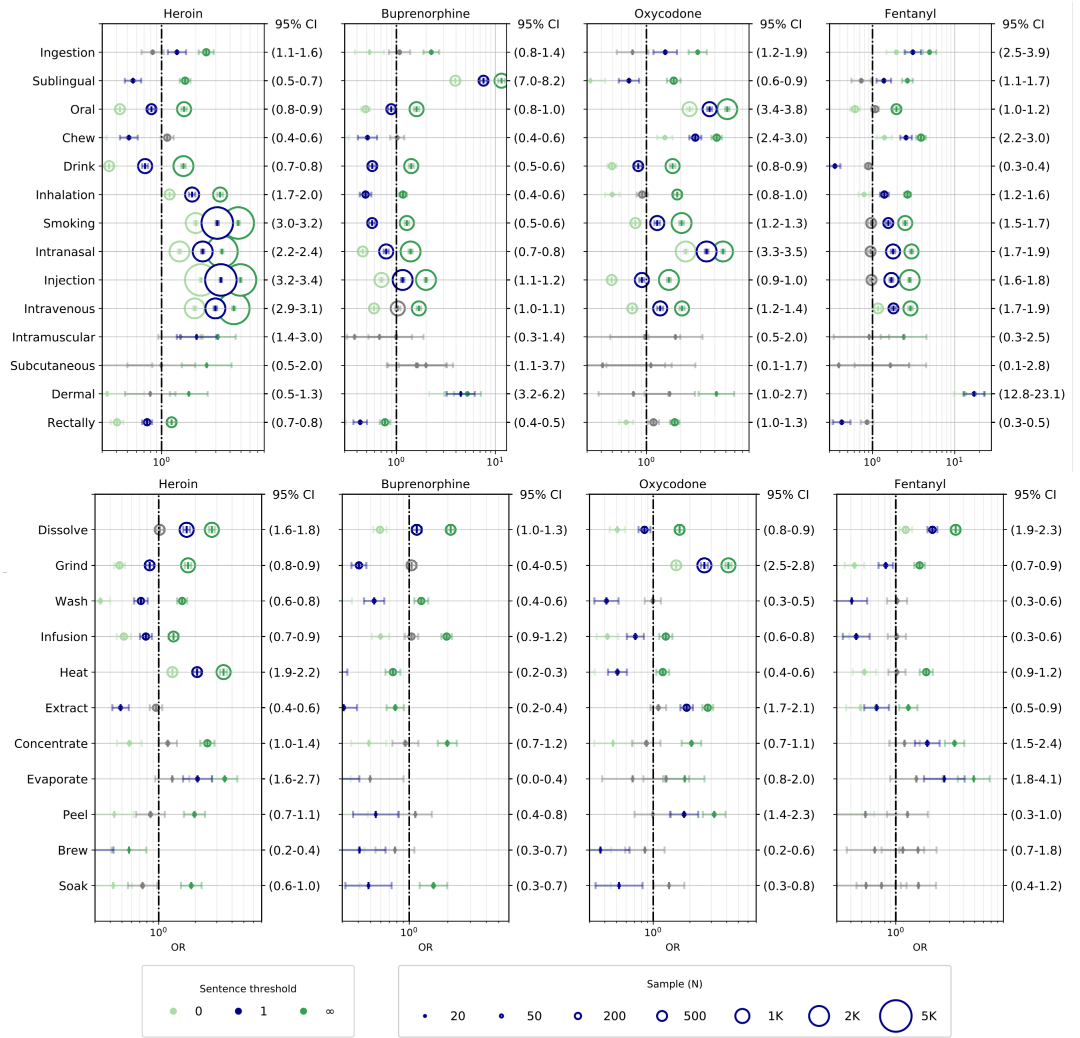


FIGURE 4.5: Odds ratios of the most widespread opioid substances with routes of administration (top row) and drug-tampering methods (bottom row). Labels on the right axis report the confidence interval at $\rho = 1$. OR: odds ratio.

odds ratio with high values, both with ROA and drug-tampering methods, meaning that the uptake of such substances happens in multiple nonexclusive ways. Our analysis shows that, for the most part, the expected medical and nonmedical routes of administration of each substance have high odds ratios (i.e., intended ROA such as ingestion of pills or known abusive administration like the injection of heroin). The oral (medical) use is often confirmed for prescription opioids (e.g., oxycodone: OR 3.6, 95% CI 3.4-3.8) while intranasal administration is often the preferred nonmedical ROA. Moreover, the use of prescription opioids has a high odd of happening by injection, primarily through intravenous administration (e.g., hydromorphone: OR 9.1, 95% CI 8.6-9.8) (Gasior, Bond, and Malamut, 2016; Omidian, Mastropietro, and Omidian, 2015). As expected, heroin appears most likely consumed through injection (OR 3.3, 95% CI 3.2-3.4) or smoked if heated up on aluminum foil (OR 3.1, 95% CI 3.0-3.2). Heroin is the only substance in our study that shows high correlations with this administration route, and it is also reported to be snorted (Surratt et al., 2017).

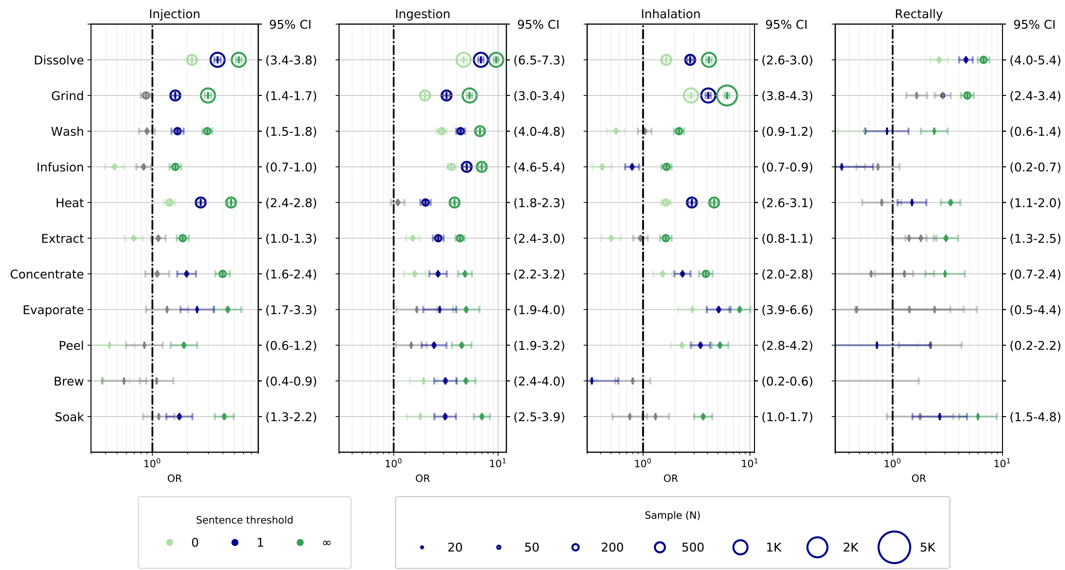


FIGURE 4.6: Odds ratios of the primary routes of administration (excluding other routes of administration) and drug-tampering methods. Labels on the right axis report the confidence interval at $\rho = 1$. OR: odds ratio.

Besides confirming and quantifying some known consumption patterns, our analysis can provide additional insights on the nonmedical use of intended routes of administration. In accordance with the literature (Kirsh, Peppin, and Coleman, 2012; Gasior, Bond, and Malamut, 2016; McCaffrey et al., 2018; Butler et al., 2013), we find evidence that misuse of prescription opioids may be associated with chewing the pills (e.g., oxycodone: OR 2.7, 95% CI 2.4-3.0). From the analysis of ROA and drug-tampering methods, it appears that nonmedical oral administration is correlated with dissolving (OR 9.7, 95% CI 9.0-10.4), grinding, and washing the substances. In some cases, oral and chewing-related misuse of prescription opioids simply consists in peeling (OR 5.1, 95% CI 2.6-9.9) the external coating, which is usually hard to chew or responsible for the extended-release effect. Even though some drug formulations, such as Opana ER (oxymorphone hydrochloride extended-release tablets; Endo Pharmaceuticals), are known to be tamper-resistant to crushing, the users can peel the tablets to get rid of the extended-release coating and reach higher recreational effects. Injection usually requires that the substance is dissolved (OR 3.5, 95% CI 3.2-3.7), while inhalation requires that the substance is ground to powder, especially for intranasal abuse (OR 6.7, 95% CI 6.3-7.1).

Ultimately, our method finds evidence of unconventional nonmedical administration for most substances. We find a high correlation between dissolving and intranasal administration (OR 4.1, 95% CI 3.8-4.4), which may indicate the adoption of "monkey water", the practice of dissolving soluble substances like tar heroin and fentanyl patches in a liquid, using the resulting liquid as a nasal spray (Ciccarone, 2009). Fentanyl patches are also consumed in other unforeseen ways; an unexpectedly high OR of fentanyl and chewing (OR 2.6, 95% CI 2.2-3.0) suggests that prescription patches intended for transdermal use may be chewed for nonmedical use. Our analyses reveal high odds of abuse of codeine (syrup) via drinking (OR 4.0, 95% CI 3.7-4.3), made by extracting or brewing the cough suppressants (OR 14.1, 95% CI 11.5-17.2) and forming the so-called lean or purple drank (Agnich et al., 2013; Hart et al., 2014; Cherian et al., 2018). Buprenorphine, usually administered sublingually in its formulations without an antagonist such as Subutex (buprenorphine; Indivior), and orally in combination with an opioid antagonist like naloxone, in the form of pills such as Suboxone (buprenorphine-naloxone; Indivior) and Zubsolv (buprenorphine-naloxone; Orexo), The measures for this substance bring evidence of a more peculiar use of buprenorphine, showing exceptionally high odds of sublingual administration (OR 7.6, 95% CI 7.0-8.2). Evidence of nonmedical use of buprenorphine is also found in the association between the method of dissolution and sublingual use (OR 18.9, 95% CI 16.8-21.3). The opioid firsthand users likely know that the opioid antagonist in buprenorphine-naloxone compounds has low bioavailability if dissolved under the tongue. Hence, to achieve higher opioid effects and eliminate the antagonist, these compounds are generally taken sublingually and not through other ROA, with which buprenorphine shows negative associations. Finally, our study shows that rectal administration is a viable and unforeseen option for the nonmedical use of some opioids, resulting in higher recreational effects, especially with hydromorphone (OR 5.2, 95% CI 4.6-6.0), morphine, and oxymorphone. Rectal administration shows high correlations with the dissolving, grinding, and soaking drug-tampering methods, possible indicators of an unconventional tampering and administration practice, largely overlooked, which involves dissolving the substances in liquid water or alcohol (i.e., "butt-chugging") (Rivers Allen and Bridge, 2017; El Mazloum et al., 2015). Subcutaneous administration is only weakly associated with morphine, suggesting that the practice of "skin popping" (Coon et al., 2005), which consists of injecting the substance in the tissues under the skin rather than into muscles or veins, is potentially not widespread.

The complex interactions between substance use, routes of administration, and drug tampering that can be unveiled with our methodology provide a broad-and-detailed perspective on the nonmedical use of opioids, evidencing abusive behaviors in which unconventional ROA and drug tampering play a key role. The added knowledge about abusive behavior that is reachable with our approach could be considered by physicians during treatment programs, allowing them to favor opioid medications that are less likely to be transformed and abused. Our results should be addressed with effective health policies, driving future clinical research to better focus its efforts on understanding health-related risks and guiding the production of new tamper-resistant and abuse-deterrent opioid formulations based on the data-drive evidence on the consumption behaviors.

4.7 Conclusions

We acknowledge some limitations that are related to the analytic pipeline. In this work, we narrowed our text analysis to term counts and co-occurrences in this work, which might have produced spillover effects in comments discussing multiple topics and could have amplified the strength of cross-associations. Future work should be devoted to including n-grams and more context-based language models. In addition, it is worth stressing that the measure of the association through odds ratios should not be intended by any means as an indication of causal effects. This work is an observational study focusing on the characterization of a complex and faceted social phenomenon rather than identifying determinants or interventions. Nevertheless, it shares the strengths and limitations of correlational studies, especially in medical research. In this chapter, we characterized opioid-related discussions on

Reddit over five years, involving more than 86,000 unique users, focusing on first-hand experiences and nonmedical use. To address the complexity of the language in social media communications, especially in the presence of taboo behaviors such as drug abuse, we gathered a large set of colloquial and nonmedical terms that cover most opioid substances, routes of administration, and drug-tampering methods. We were able to characterize the temporal evolution of the discourse about opioid uptake and identify notable trends, such as the surge in the popularity of fentanyl and the decrease in the relative interest in heroin. Focusing on routes of administration, we extended the current pharmacological and medical research with an in-depth characterization of how opioid substances are administered since different practices may imply different effects and potential health-related risks. We proposed a 2-layer taxonomy and corresponding vocabulary that enabled us to study both medical and recreational routes of administration. We uncovered the presence of conventional nonmedical ROA like intranasal administration and intravenous injection and the spread of less conventional practices such as an increasing trend in rectal use. In particular, we characterized for the first time at scale the phenomenon of drug tampering regarding nonconventional ROA, which could impact health outcomes since it alters the pharmacokinetics of medications. The interplay between these dimensions was systematically characterized by quantitatively measuring the odds ratios, providing an insightful picture of the complex phenomenon of opioid consumption as discussed on Reddit.

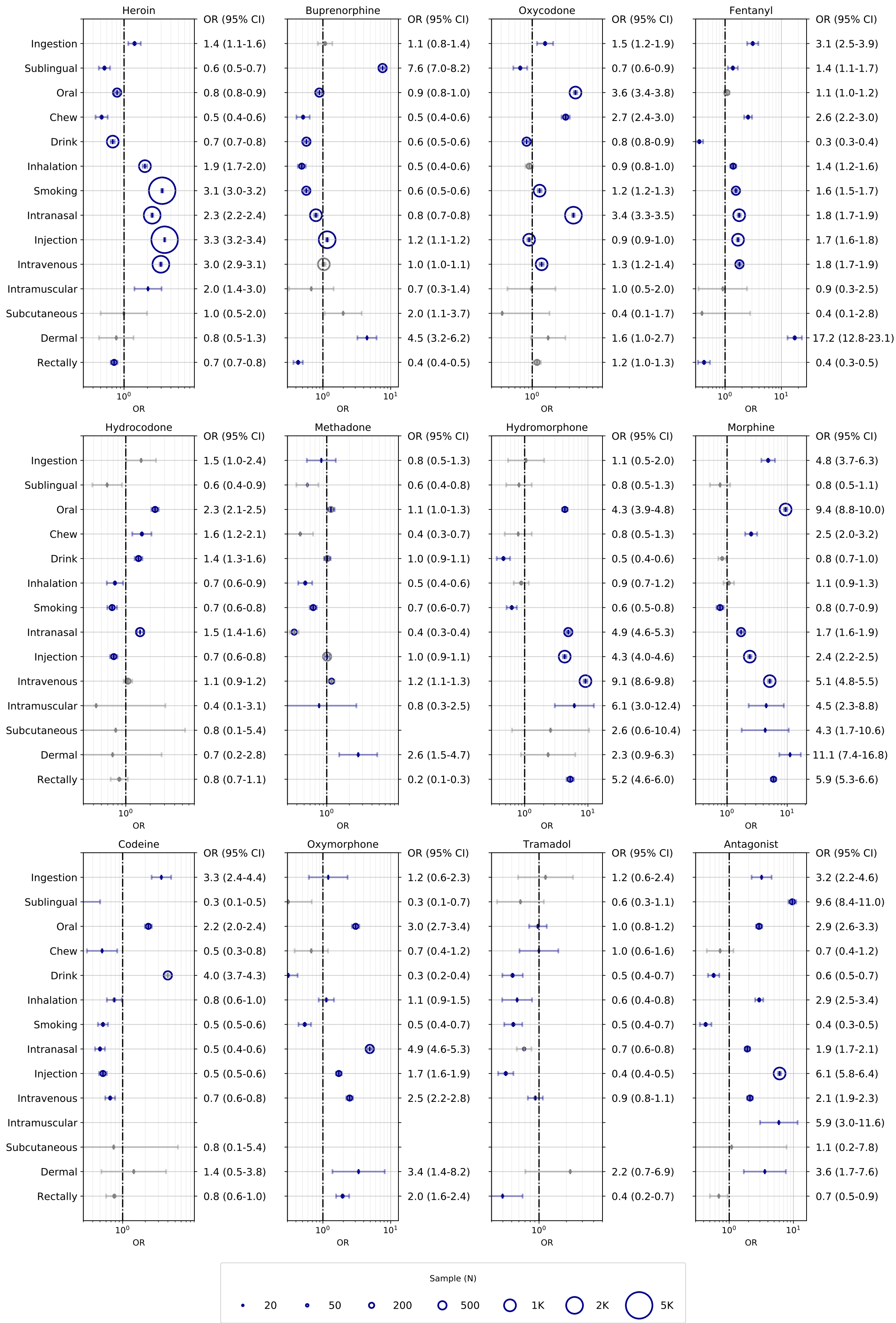


FIGURE 4.7: Odds Ratios of opioid substances and Secondary Routes of Administration. The central line and the bar mark the OR and the 95% confidence interval, respectively, while the circle size is proportional to the sample of co-mentions. Measures that are not statistically significant (P >.01) are reported in gray. Labels on the right axis report the Odds Ratio and the confidence interval.

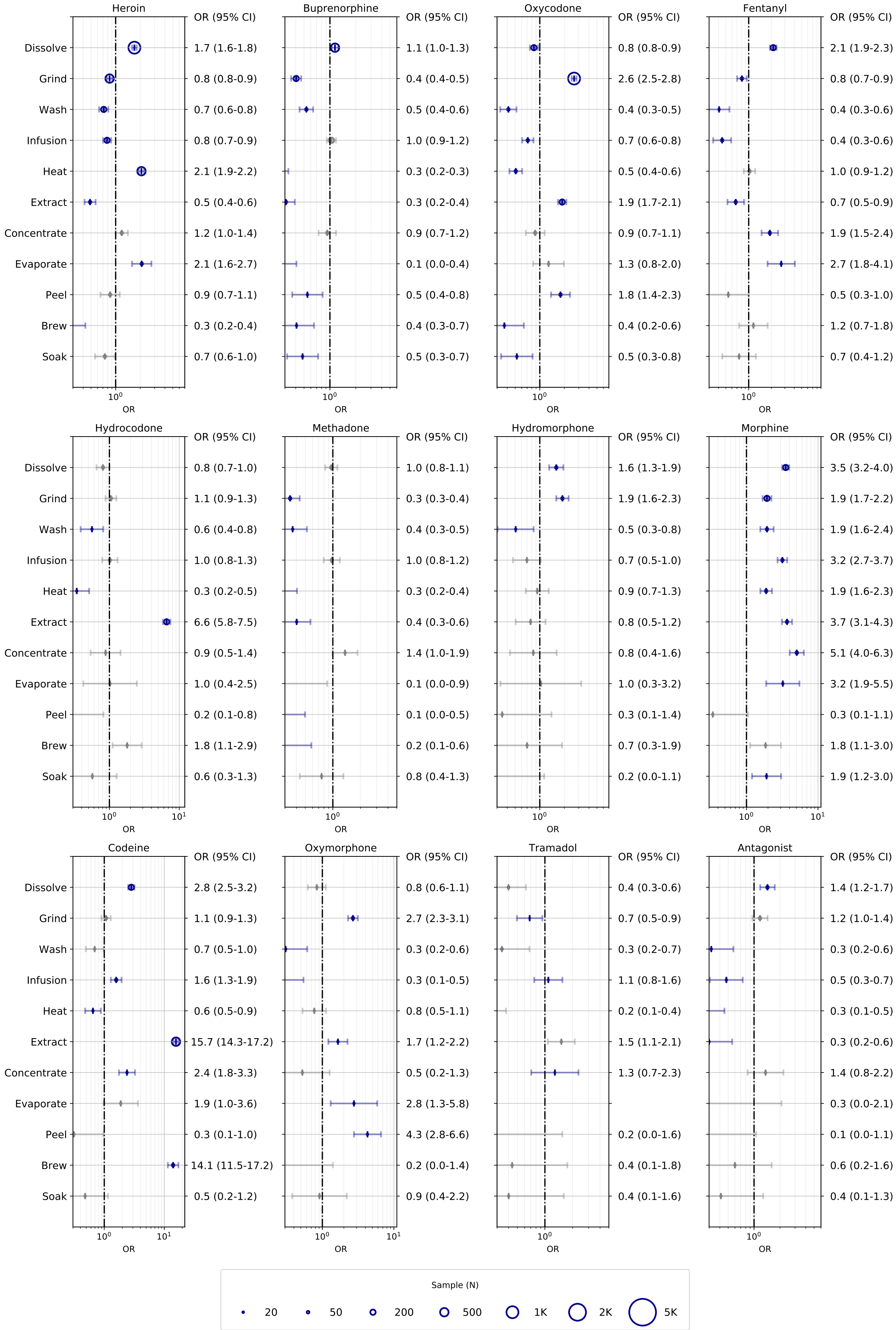


FIGURE 4.8: Odds Ratios of opioid substances and Drug Tampering Methods. The central line and the bar mark the OR and the 95% confidence interval, respectively, while the circle size is proportional to the sample of co-mentions. Measures that are not statistically significant (P >.01) are reported in gray. Labels on the right axis report the Odds Ratio and the confidence interval.

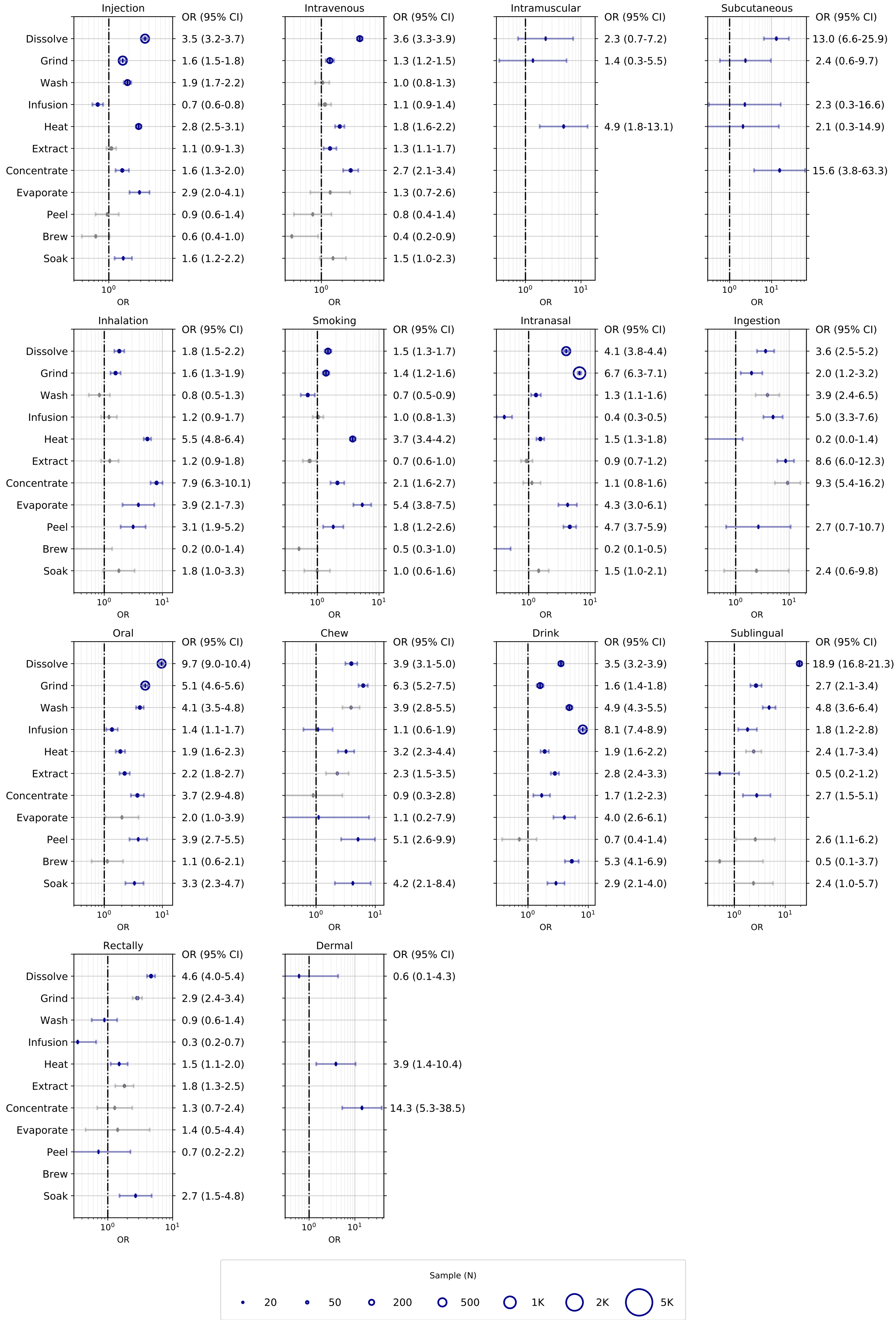


FIGURE 4.9: Odds Ratios of Secondary Routes of Administration and Drug Tampering Methods. The central line and the bar mark the OR and the 95% confidence interval, respectively, while the circle size is proportional to the sample of co-mentions. Measures that are not statistically significant (P >.01) are reported in gray. Labels on the right axis report the Odds Ratio and the confidence interval.

Chapter 5

Characterizing online peer support to recovery

5.1 Scope

Opioid Use Disorder, formerly known as Opioid Abuse or Opioid Dependence, is a chronic condition diagnosed in patients based on the American Psychiatric Association DSM-5 criteria (American Psychiatric Association, 2013). In this framework, patients must show at least two of the following marks within a 12-month period to be confirmed with a diagnosis of OUD:

- Opioids are often taken in larger amounts or over a longer period than was intended.
- There is a persistent desire or unsuccessful efforts to cut down or control opioid use.
- A great deal of time is spent in activities necessary to obtain the opioid, use the opioid, or recover from its effects.
- Craving, or a strong desire or urge to use opioids.
- Recurrent opioid use resulting in a failure to fulfill major role obligations at work, school, or home.
- Continued opioid use despite having persistent or recurrent social or interpersonal problems caused or exacerbated by the effects of opioids.
- Important social, occupational, or recreational activities are given up or reduced because of opioid use.
- Recurrent opioid use in situations in which it is physically hazardous.
- Continued opioid use despite knowledge of having a persistent or recurrent physical or psychological problem that is likely to have been caused or exacerbated by the substance.
- Exhibits tolerance.
- Exhibits withdrawal.

Breaking out of the recurrent use of opioids, ignoring the cravings, and overcoming withdrawal symptoms require will and endurance that are challenging to reach without help. The participation to *peer support groups*, as well as other nonpharmaceutical interventions such as counseling, is a crucial component of successful remission from opioid use. Unfortunately, many individuals may face barriers to access to peer support treatment, such as shame and social stigma, seclusion, or mobility restrictions.

This chapter aims to quantitatively characterize the Reddit community's potential in offering these individuals an online option to receive peer support and acknowledgment. To answer these research questions, we focus on a group of Reddit authors that publicly disclosed the beginning of their recovery process from opioid use. In particular, we implement a computational pipeline with natural language processing and statistical tools to investigate the interactions between these users and the Reddit community and characterize their social behavior. In this work, we identify more than 2k who explicitly disclose the timeline of their recovery process on the platform. First, we infer the day in which they started to recover. Then, we analyze their social behavior from two months before to two months after the start of recovery by aligning their posting timelines according to the respective recovery starting date. We analyze the content of their interactions on the platform, uncovering the presence of peer support dynamics such as the exchange of Support, Trust, Status, and the sharing of similar experiences in a specific recovery-oriented community, `r/OpiatesRecovery`. These social dynamics suggest that Reddit users who begin opioid use recovery consider this community a safe place to find support and indicate that the Reddit community is attentive and fit to respond to the support needs of its participants. Moreover, using Interrupted Time Series analysis (ITS), we find that similarly to peer support groups, the supportive behavior of this community encourages the recovering users to change personal behavior and social groups, leading them to abandon opioid-consumption-related communities. Lastly, we highlight which types of online social interactions impact the most on the engagement and the attachment of the authors to the recovery community. We find that recognition, acknowledgment, and the exchange of Knowledge and support are the most relevant factors in driving the recovering individuals to keep the relationship with the recovery community open.

5.2 Data preparation

In this chapter, we analyze the textual part of the submissions and the comments publicly available data from 2015 to 2019. In particular, we collect a random sample of 1000 submissions on `r/OpiatesRecovery` to train a machine learning model for classification (described in the following chapter). This model enables us to select $N = 2125$ Reddit authors in recovery (referred to as *recovering authors* in the following) and the date of their start of recovery. The complete dataset used for analysis consists of 265k submissions and comments produced by over 8000 pseudonymous Reddit authors in recovery, as well as all comments to those posts written by the rest of the community (referred to as *community* in the following) as a response.

5.3 Estimating the start of recovery

In this chapter, we focus on the digital cohort of *recovering authors*, a group of Reddit authors that begin their process of recovery from opioid use disorder, and who publicly disclose the progress of their recovery with the Reddit community.

In particular, in this section we describe how to use a mix of machine learning and regular expression to estimate the starting date of recovery t_0 for a large number of authors in the `r/OpiatesRecovery` community. The pipeline to assigning each recovering author a t_0 is composed of three stages:

- we collect a sample of submissions where we manually identify whether the author self-reports the time elapsed since beginning recovery;
- we use the annotated dataset to train a machine learning model in order to identify submissions of this type among all the available ones;

- we use regular expressions to estimate the starting date of the recovery process for each recovering author.

5.3.1 Temporal expressions of recovery.

First, we create a small hand-curated dataset to build our model. We collect a random sample of 1000 user submissions on `r/OpiatesRecovery`. We manually check the submission's title for the presence of self-reports of recovery that include references to the time elapsed since its beginning. Specifically, we annotate as positive examples the posts referring to personal and firsthand experiences of recovery that also contain clear temporal marks indicating the time spent in recovery, e.g., *"Today I'm two weeks clean"*. We annotate all the other posts as negative examples, including those who refer to the detoxification of others, to relapses, or those related to other subjects. This annotation process produces 223 positive posts and 777 negative ones. We split this set into two stratified datasets for training and validation that contain respectively 70% and 30% of the examples while preserving the positive-negative ratio. Then, we use the labeled dataset to train and test a machine learning model capable of identifying submissions containing self-reported recovery periods. To obtain the best possible outcome, we test the classification performance of 4 well-established machine learning models for text classification, implemented in Scikit-learn (Pedregosa et al., 2011), reported in Table 5.1.

We perform model selection on the training dataset with 5-fold cross-validation and grid-search for hyper-parameter tuning. Given the class imbalance in both the training and validation sets, we choose the F1-score as the target performance metric.

As a text preprocessing step, we remove punctuation, and we perform lemmatization with the NLTK implementation of *wordnet* (Bird, Klein, and Loper, 2009). We also automatically transform to digits the text snippets referring to numeral quantities by using the *text2digits* library (text2digits, 2021). Then, we transform the preprocessed corpus of texts into a numerical vector representation of word frequencies by using a bag-of-words representation with optional *tf-idf* weighting.

Optionally, prior to the text vectorization step, we mask the words referring to known time expressions with a unique time-expression token to allow the model for more generalization. To do so, we develop a series of regular expression rules to match expressions that contain a reference to a certain number of hours, days, weeks, months, and years, such as *"Day 5"*, *"2 months"*. We also account for complex forms which may contain unrelated terms, e.g., *"1 painful week"*.

Model selection results are reported in Table 5.1. Based on the best validation performance of $ROC\text{-}AUC = .942$ and Matthew's correlation coefficient Boughorbel, Jarray, and El-Anbari, 2017 $MCC = .847$ we select the pipeline consisting of time-expression masking, tf-idf weighting, and logistic regression as the most suitable for our task. After retraining the best model on the entire training set, we use it to predict a score on all the remaining unlabelled submissions produced by Reddit users on `r/OpiatesRecovery`. Out of the 18,186 total samples, 4227 submissions (23%) are predicted as positive by our model, i.e., with a high probability of the presence of recovery declaration and specific mention to time spent in recovery.

5.3.2 Extraction of temporal references

Next, we focus on isolating the textual expressions regarding the time elapsed while in recovery and on converting them into their numeric equivalent t_d expressed in

Model Classifier	Model Parameters	Time expr. mask	Text Vectorizer	ROC-AUC	F1	Accuracy	Precision	Recall	MCC
Logistic Regression	C: 10, Penalty: L2, Solver: lbfgs	✓	tf-idf	0.942	0.881	0.943	0.829	0.940	0.847
Random Forest	Criterion: Gini, N. Estimators: 100	✓	count	0.939	0.859	0.930	0.780	0.955	0.820
Decision Tree	Criterion: Entropy	✓	tf-idf	0.919	0.841	0.923	0.782	0.910	0.795
Support Vector Machine	C: 1, Gamma: scale	✓	tf-idf	0.914	0.866	0.940	0.866	0.866	0.827

TABLE 5.1: Performance metrics for model selection results, evaluated on the validation set. For each model, the table reports the best hyper-parameters for the models, and the pipeline regarding time expression masking and text vectorization.

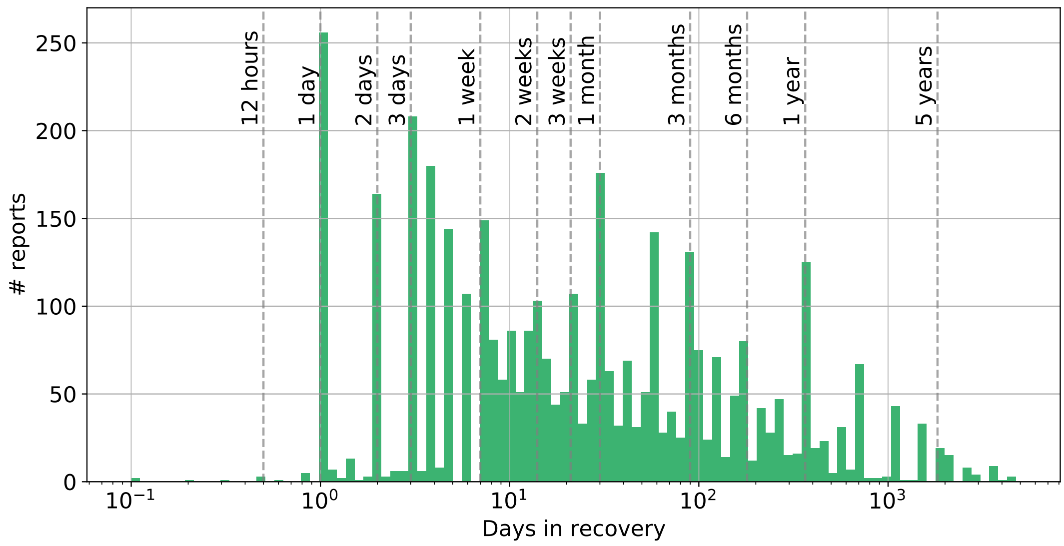


FIGURE 5.1: Number of reports containing the elapsed time since beginning recovery as declared by the recovering authors. The bins of the histogram are evaluated following a logscale progression. Vertical dashed lines report some reference elapsed times.

days.

We apply a series of regular expressions rules to capture the numerical part n of textual expressions containing reference to an elapsed time. We convert each post p in a vector $n_p = [n^h, n^d, n^w, n^m, n^y]_p$ which contains the number of *hours*, *days*, *weeks*, *months*, and *years* expressed.

Then, we transform each component in the corresponding equivalent in days. For simplicity, we standardize the duration of the months to 30 days and that the years to 365 days. We proceed to assign a final *recovery time* t_d in days to each post. For posts containing only one time expression, we output the sum of the components of n_p in days. In case a post contains multiple time expressions, we identify the following heuristic: if the time expressions are tied by conjunction, e.g., *"1 week and 4 days"*, we sum the two vectors; in case of multiple expressions separated by *"in"*, *"after"*, *"from"*, or *"for"*, we consider only the first time expression; in all other cases, we discard the submission.

We report in Figure 5.1 the distribution of all the extracted t_d in days. We observe that the reports cluster around important temporal recovery milestones: every day of the first week, then the weeks, followed by the months, and finally the years.

Our procedure finds 3805 submissions which contain an expression of recovery time t_d, belonging to 2125 distinct Reddit users (26% of the total users who created at least one submission on `r/OpiatesRecovery`).

5.3.3 Estimate of recovery time

To estimate a candidate date t_0 at which the author of a post started the recovery process, we subtract t_d days from the creation date of the submission.

Each recovering author might have written multiple submissions containing recovery progress, either referring to the same recovery period or multiple separate ones. Therefore, we associate a set of candidate recovery starting dates to each author, one for each submission.

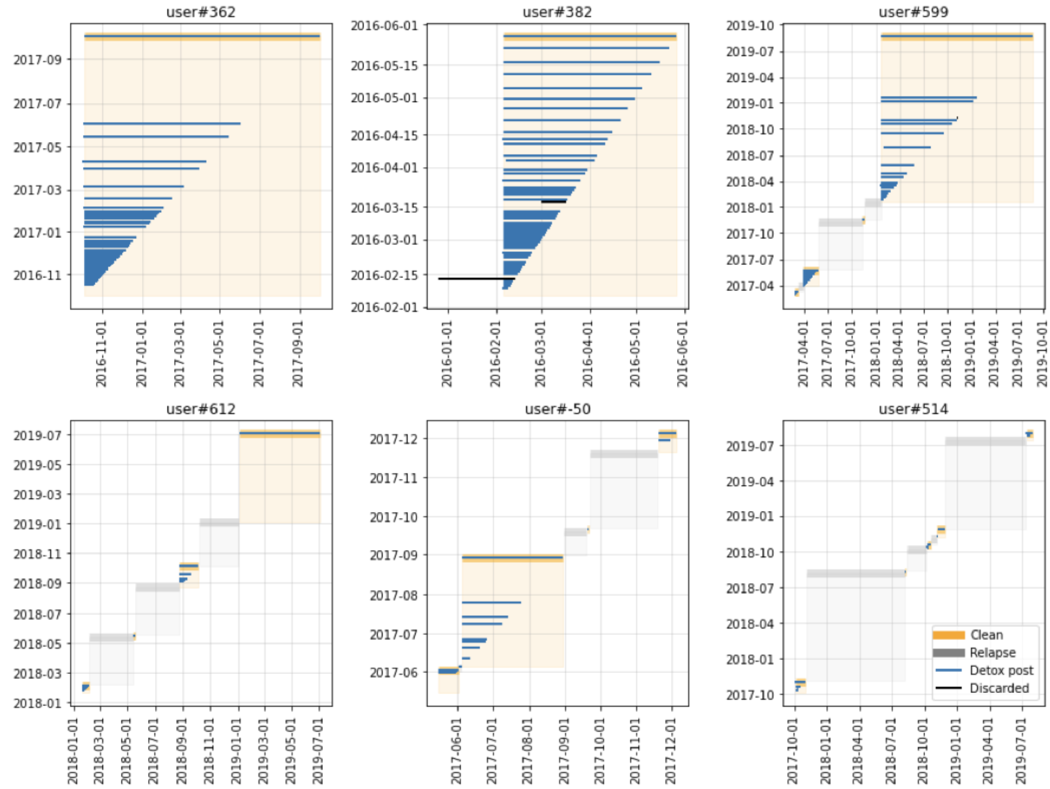


FIGURE 5.2: Time elapsed from the recovery report and the begin of recovery for six random recovering authors. The thin bars represent the time elapsed between the creation of a post containing a declaration of recovery (right end of a bar) to the estimated begin of recovery (left end of a bar). Black bars are considered outliers and are discarded by the clutering algorithm. The coloured areas represent groups of declarations of recovery that are considered to be pointing to the same t_0 by the clustering method.

Since the estimation of the t_0 from a submission can suffer from errors introduced both by our pipeline and by unclear reporting, we rely on DBSCAN (Ester et al., 1996), a well-established density-based clustering procedure, to identify consistent reports and to discard outliers. In this paradigm, a cluster identified by the algorithm for a recovering author represents a set of reports consistently pointing at a temporal neighborhood around the same t_0, and the outliers represent spurious or incorrect reports. Those t_0 reported only once, but are not in conflict with other consistent periods, are accepted. To account for increasing estimation or reporting errors for longer reported recovery elapsed times, we set the DBSCAN parameter ϵ, i.e., the neighborhood radius for a cluster to include new points, proportional to the t_d of each post. Finally, we select the most frequent t_0 in each cluster as the representative recovery starting date. The temporal span that goes from t_0 to the posting date of the last submission associated with the same cluster identifies an uninterrupted period of abstinence from substance use experienced by the recovering author. Hence, in the case of overlapping recovery periods, we discard the period with fewer reports, i.e., the more uncertain one. Since OUD is clinically considered a chronic disease, people who suffer from it might slip back into relapse periods, i.e., the return to substance use after a period of recovery. We can find this behavior also in our cohort, where some authors (302 out of 2125) report multiple non-overlapping recovery periods, separated by periods in which relapse may have occurred. In the case of multiple recovery periods reported by the same author, we consider only the first one in all the analyses. Figure 5.2 shows a graphical representation of the periods of recovery and (possibly) relapse for six randomly picked recovering authors. In the figures, the thin lines represent the time elapsed from the creation of the post containing an expression of recovery to the estimated t_0, color-coded in blue if considered consistent by the clustering algorithm, and in black if outliers. The shaded areas indicate the coherent phases of recovery, in green the consistent periods of abstinence from drug use, and in gray the periods in which relapse might have occurred.

5.4 Behavioural fingerprinting

In this section, we create a fingerprint of the behavior of the recovering authors and their interactions with the Reddit community, and we characterize the potential of Reddit as a peer support group. Specifically, in this section we quantify the presence of characteristics proper of a peer support group in the conversations of these authors with the community, and we measure potential shifts in their behavior around the starting day of recovery t_0. Similarly to Fan et al. (2019) and ElSherief et al. (2021), we align the individual timelines of the users according to a point-wise event, and we aggregate some metrics evaluated on the aligned timelines to observe temporally-resolved population-level measures. Specifically, we collect the posting activity of each recovering author in a time window of 60 days before and after the respective starts of recovery t_0. We also include all the comments written by the community in reply to those posts. We remove all the posts in which the recovering authors disclosed their elapsed time in recovery, not to introduce biases due to data collection. Finally, we align the authors' timelines by offsetting each one to its respective start of recovery t_0, i.e., we express each timeline in a range of $t \in [-60, 60]$ days. Next, we evaluate a series of daily measures y_t, described in detail below, by using either the content or the posts' metadata on a given day. Based on existing literature, we consider two different types of measurements, which reflect two aspects of the behavior of users: the content of their social interactions, measured by the identification of the ten social dimensions of conversation using recurrent neural networks, and their engagement, measured by evaluating several metrics based on their posting activity. To quantify the presence of shift in the behavior of the recovering authors and the community around the starting day of recovery t_0, we apply two different methodologies, explained in detail below. Both methods consider all the data points and provide estimates at the population level but aggregate the data differently. The first, *Average Behavioral Shift*, enables to control for single user's behavior, and the second, *Average Behavioral Shift*, for longitudinal behavior.

5.4.1 Building behavioural features

The first category of measurements we implement considers the types of interactions happening among the recovering authors and the community. These features reflect our aim to measure changes in social feedback and peer-support experienced during recovery. We rely on a set of Long short-term memory (LSTM) neural network classifiers implemented by Choi et al. (2020). The models are pre-trained on a corpus of Reddit posts to determine the binary presence in the posts of ten basic *social dimensions of conversation and relationships* (Deri et al., 2018). Table 5.2 reports a brief description of the ten social dimensions, along with some modified examples of posts present in our dataset containing the respective social dimensions. Given a textual input, each of these recurrent neural network classifiers outputs a score between 0 and 1, reflecting the presence of one of the said social dimensions. As discussed in Section 4.6, the length of the posts in Reddit may vary greatly, and the posts may consist of multiple sentences. Hence, given the better performances of the classifiers with medium-sized text, we split each post/comment into sentences. Then, we assign a score to each sentence for every dimension of conversation using the classifiers. For each post/comment, we max-pool the scores of its sentences to compute the final score relative to each dimension of conversation.

We apply a custom transformation to the scores to determine the social dimension's binary presence in each post. Since the classifiers are trained on general-purpose corpus and might have different output sensitivities on the posts at study, one must be cautious when considering the output score as the crude probability of presence of a social dimension in a post. In order to account for this, rather than estimating an optimal threshold on the score for each social dimension, i.e. classifier, we adopt an approach that mitigates their intrinsic biases: we evaluate the quartiles of the distribution of all the scores produced by the classifier for each specific social dimension and binarize the scores based on their membership to the last quartile. In this work, rather than estimating the crude quantity of the social dimensions exchanged, we aim at evaluating their changes and the evolution in time in a comparative way. For this reason, the thresholding approach proposed is better suited for our analytical framework.

Finally, we report for each author the daily fraction of posts that contain each dimension over the total number of daily posts, representing the daily aggregate relative measure of the social dimensions exchanged.

The second category of behavioral features corresponds to activity-related measures, from which we can observe social group change and shifts in personal engagement in the recovery community.

To evaluate these activity-related features, we rely on the metadata of the posts collected, which include the score and the subreddit of the posts created by the recovering authors and the subreddit and the author of the comments. We follow a similar procedure to the one adopted for evaluating the social dimensions of conversation: we group the posts and the comments created or received daily by each recovering author, and we provide daily measures of the activity-related features. In particular, we evaluate the number of posts/comments created or received (*N. Posts*), the number of unique subreddits where the authors have posted (*N. Subreddits*), and the number of unique authors with whom the recovering authors interacted (*N. Contacts*). Moreover, we break down their activity on specific subreddits, i.e., `r/opiates` and `r/OpiatesRecovery`, by computing the ratios of posts and comments on these subreddits w.r.t. the total number of posts of each author in the day (respectively, *Share Opiates* and *Share OpiatesRecovery*). Similarly, we compute the relative share of interactions with unique users on `r/opiates`, on `r/OpiatesRecovery`, and on all the other subreddits combined (respectively, *Share Contacts Opiates*, *Share Contacts OpiatesRecovery* and *Share Contacts Other*). We do so by counting the unique users who commented on the authors' posts, broken down by subreddits, In addition, as measures related to social feedback, we evaluate the daily sum of the scores assigned to the posts (*Sum. Scores*) and the daily average valence of the posts created or received, computed by using the VADER (vaderSentiment, 2021) package. To avoid potential biases caused by various levels of baseline engagement of the users with the platform, e.g., users with a different baseline posting activity on Reddit, we

Social dimension	Definition	Example
Support	Giving emotional or practical aid and companionship (Fiske, Cuddy, and Glick, 2007)	Hope you will to sort it out soon! – I suggest to all others who are struggling, to post on here daily to help you stay focused.
Trust	Will of relying on the actions or judgments of another (Luhmann, 1982)	I want to make her proud and I'm not going to let her or myself down. – It's been a good day, feeling that restless legs aren't too bad and I'll have a good night.
Similarity	Shared interests, motivations or outlooks (McPherson, Smith-Lovin, and Cook, 2001)	When I am doing something I feel normal, but when I sit around it really is the only thing on my mind. – Now that is just my own personal experience but I think a shit load of addicts feel the same.
Status	Conferring status, appreciation, gratitude, or admiration (Blau, 1964)	Just wanted to say it to you, good work. – Well done, keep it up!
Power	Having power over behavior and outcomes of another (Blau, 1964)	Been to 7 meetings in the last 5 days. Start work again tomorrow. – Keep up the good work!
Fun	Experiencing leisure, laughter, and joy (Argyle, 2013)	If I can pass every class while practically stoned, I must be a god while sober. This is hilarious. – My indoor cat makes me happy, he gets pretty stupid whenever he has the opportunity to eat plants.
Conflict	Contrast or diverging views (Tajfel et al., 1979)	It hurts me to know that nobody sponsors me. – We generally hide behind an image of being badass when in actuality we can't even tolerate the most minor symptoms from withdrawal.
Knowledge	Exchange of ideas or information; learning, teaching (Fiske, Cuddy, and Glick, 2007)	I was taking small doses (15-22.5mg) of DXM twice a day, I read about the positive results it has on opiate withdrawal in a clinical research trial. – Only used recommended dosage of lope for the constant shits of the first week, didn't try to use it to suppress withdrawal suffering.
Romance	Intimacy among people (sentimental or sexual) (Buss, 2003)	You were a genuinely beautiful soul. – I love you people.
Identity	A shared sense of belonging to the same group (Tajfel, 2010)	Spent everything to be there as it is the greatest affirmation of her faith, as being a good catholic? – Strength, freedom, autonomy, are all characteristics of people that find sobriety.

TABLE 5.2: Social dimensions description and examples.

normalize the measures based on raw counts (e.g., number of posts, number of contacts) by computing z-scores considering the entire timeline of each author. Table 5.3 reports a summary of the activity-related measures.

Name	Description	*z-score*
N. Posts	Daily total number of posts created/comments received	✓
Share Opiates	Daily share of posts created/comments received on r/opiates	
Share OpiatesRecovery	Daily share of posts created/comments received on r/OpiatesRecovery	
Avg. Valence	Daily average of the Valence of the posts created/comments received	
Sum Scores	Daily sum of the scores (upvotes - downvotes) assigned to the posts created	✓
N. Subreddits	Daily number of subreddits with authors' posting activity	✓
N. Contacts	Daily interactions with unique authors	✓
Share Contacts Opiates	Daily share of interactions with unique authors on r/opiates	
Share Contacts OpiatesRecovery	Daily share of interactions with unique authors on r/OpiatesRecovery	
Share Contacts Other	Daily share of interactions with unique authors on other subreddits	

TABLE 5.3: Activity-related measures of behaviour.

5.4.2 Statistical assessment of behavioural shift

Our dataset consists of numerous cross-sectional observations of metrics of behavior corresponding to multiple authors, spanning from two months before the beginning of recovery to two months after. To quantify the presence of shift in the behavior of the recovering authors and of the community around the starting day of recovery t_0, we apply two different methodologies, explained in detail below. Both methods consider all the data points and provide estimates at the population level but aggregate the data differently. The first, *Average Behavioral Shift*, enables to control for single user's behavior, and the second, *Average Behavioral Shift*, for longitudinal behavior.

Average Behavioral Shift

We statistically assess the average presence of shift in behavior by evaluating the *Average Behavioral Shift*. The purpose of this measure is to quantify how much a said behavior has changed –on average at the population level– when comparing the recovery period to the one before, controlling for the behavior of every single user. This measure first considers the average shift in each user's behavior by comparing the average values of a particular metric computed before and after his start of recovery. Then, it provides the typical shift at the population level by averaging the shifts of all the users. It is formally defined as:

$$\delta_y = \frac{1}{|U|} \sum_{i \in U} \bar{y}^i_{t \geq t_0} - \bar{y}^i_{t < t_0} \tag{5.1}$$

where $\bar{y}^i_{t \geq t_0}$ and $\bar{y}^i_{t < t_0}$ are the average values of the measure y_t for user $i \in U$, respectively after and before the beginning of recovery, and U is the set of all recovering authors. Shuffling the authors' timelines for $B = 1000$ rounds of bootstrap, we evaluate p-values to check for the statistical significance of each average shift δ_y.

Interrupted Time Series

To understand how the behavior of the individuals who started opioid use recovery changes throughout the process, we employ an Interrupted Time Series analysis (ITS) (McDowall, McCleary, and Bartos, 2019). ITS is a quasi-experimental technique that allows the estimation of the causal effect of an intervention happening at a defined time in the absence of a counterfactual. Thanks to its inferential powers, ITS have been widely adopted for assessing the effects of health and policy interventions (Bernal, Cummins, and Gasparrini, 2017; Chandrasekharan et al., 2017; Tian and Chunara, 2020; ElSherief et al., 2021). In our study, we consider the start of recovery t_0 as the intervention, and we investigate its effect on the time series of behavior y_t. After the alignment of the timelines of the authors on t_0, for each dimension y_t, we fit an Ordinary Least Squares (OLS) regression model described as

$$y_t = \beta_0 + \beta_1 t + \beta_2 D_t + \beta_3 P_t \tag{5.2}$$

with

$$D_t = \begin{cases} 0 & t < t_0 \\ 1 & t \geq t_0 \end{cases} \quad P_t = \begin{cases} 0 & t < t_0 \\ t & t \geq t_0 \end{cases}$$

where D_t is a dummy variable with a null value before the start of recovery, and P_t is the progressive time in recovery in days.

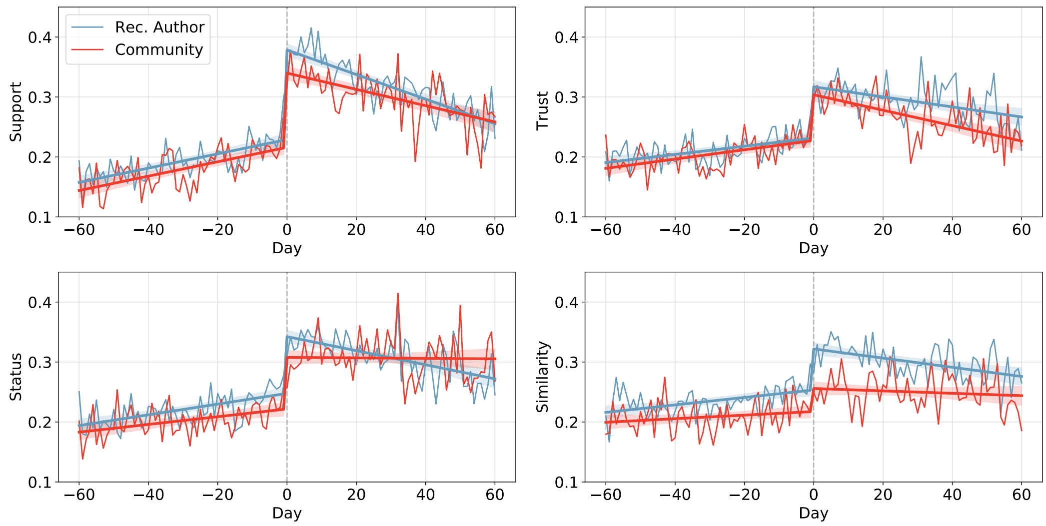
To clarify the interpretation of this analysis, we report an example case. Considering a measure y_t such as the *Support* received from the community, the regression coefficients β_0 and β_1 reflect respectively the pre-recovery level of *Support* exchanged and its trend approaching t_0; the coefficient β_2 quantifies the immediate effect of the intervention, i.e., the quantity of immediate *Support* received at the start of recovery; finally, β_3 reflects the trend change that *Support* follows during recovery. Moreover, the assessment of the statistical significance of the coefficients of the models enables to clarify if the presence of the intervention influences the effects associated with the coefficient (e.g., the intervention has no immediate effect on the phenomenon studied if the p-value associated with the coefficient β_2 is not statistically significant).

5.4.3 Presence and evolution of peer support

We apply the natural language processing pipeline described above to the textual content of the discussions involving the users who started recovery to find the hallmarks of peer support. We use the LSTM classifiers to identify the ten social dimensions that are the building blocks of conversations and relationships. We test the presence of a shift in the social dimensions with the two methodologies described.

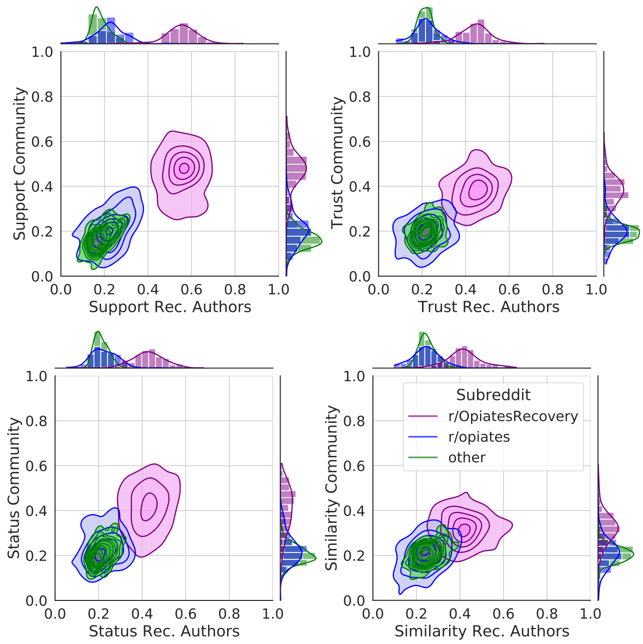
Figure 5.3b shows the *average behavioral shift* δ_y, i.e., the population-average difference in the exchange of a social dimension y between the periods after and before the start of recovery t_0. The measure uses the fraction of daily posts containing a specific social dimension in each period.

In blue, we show the quantities related to posts written by the recovering authors, and in red, those related to the posts written by the rest of the community as a response. We find a positive average shift with a strong statistical significance ($P < 0.001$) in the exchange of the social dimensions that can be related to peer-support, namely *Support*, which increases the most (8% on average), followed by *Trust*, *Status*, and *Similarity*. The shifts in the exchange of these social dimensions present highly matching behaviors across the two directions of conversation, from



(A)

(B)



(C)

FIGURE 5.3: Interrupted time series (a) and Average behavioral shift (b) of the social dimensions of conversation regarding the authors and community, respectively reported in blue and red. In (a), the thin lines report the daily average of the studied social dimensions, in a temporal span ranging from two months before to two months after the start of detox t_0. The thick lines represent the corresponding ITS fits, with 95% confidence intervals as shaded areas. In panel (b) dots correspond to the average value $\bar{\delta_y}$ and bars report the Standard Error of the Mean (SEM). Values not statistically significant ($P \geq 0.05$) are indicated with hollow markers and gray bars. The plots in panel (c) show the distribution of daily averages of the share of authors' and community posts containing certain social dimensions. The plots report the bivariate distributions relative to the three communities at study, shown as kernel density plots, with the marginal authors' and community's distributions on the axes.

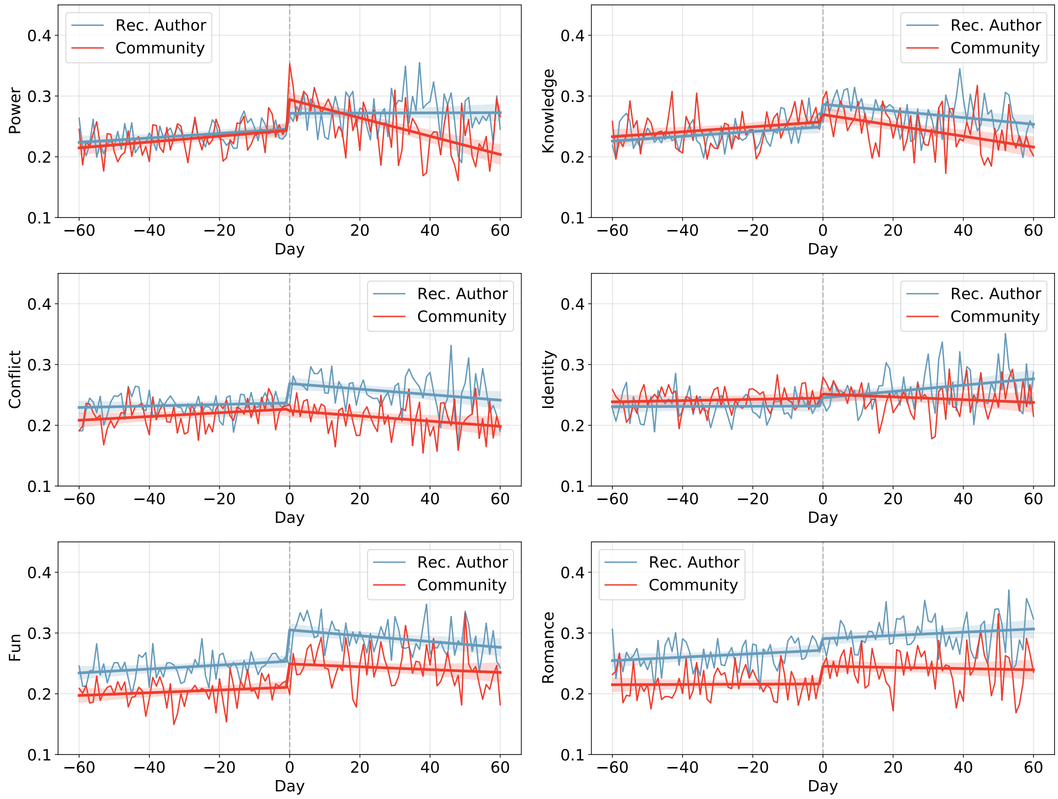


FIGURE 5.4: Interrupted time series of the social dimensions of conversation regarding the authors and community, respectively reported in azure and red. The thin lines report the daily average of the studied social dimensions, in a temporal span ranging from two months before to two months after the start of detox t_0. The thick lines represent the corresponding ITS fits, with 95% confidence intervals as shaded areas.

the recovering authors to the community and vice versa. The social content the recovering authors receive from the community generally shows more important positive shifts for these social dimensions, meaning that on average, the supportive behavior of the community changes to a more considerable extent subject to the beginning of the recovery of some of its users. A likely explanation for this phenomenon is that the authors in recovery *shift* their interactions towards the more supportive communities. We do not find statistical evidence of a shift in the exchange of the other dimensions of conversation such as *Knowledge*, *Power*, *Romance*, and *Identity*. The results of the average behavioral shift regarding the social dimensions of conversation are reported at the end of this section in tabular form in Table 5.4.
Interrupted time series (ITS) analysis confirms these results and provides further details on their temporal unfolding. Figure 5.3a, and Figure 5.4, report the daily average of the social dimensions analyzed as well as the corresponding ITS fits, in a temporal span ranging from two months before to two months after the start of recovery t_0. In particular, Figure 5.3a shows the ITS results of the four most relevant social dimensions of conversation to characterize the evolution of peer support. Both directions of exchange of *Support*, *Trust*, and *Status*, along with the *Similarity* dimension expressed by the authors, exhibit similar behavior: a slight but significant ($P < 0.001$) increasing trend approaching t_0, followed by a strong significant

($P < 0.001$) positive shift at the start of recovery (e.g., +14.9% for *Support*). As the recovery progresses, the exchanges of *Support* and *Trust* return to their baseline levels at a faster rate compared to the growth measured before the t_0. The exchanges of *Power* (Figure 5.4) and *Status* interactions, i.e., the affirmation of Power over behavior followed by conferred appreciation, show a significant positive increase at t_0 with opposite matching dynamics afterward: on the one hand, the *Status* expressed by the recovering authors matches the *Power* received from the community, with a decreasing trend during recovery; on the other hand, the *Power* expressed by the authors is matched by *Status* received from the community. Both dimensions show a steady behavior throughout recovery after a substantial and significant positive shift at t_0. In the ITS analysis, we measure lower levels of significance or no significance for the shifts in the exchange of *conflict*, *Knowledge Romance*, and *Identity*. For completeness, Table 5.5 at the end of the section reports values and statistical significance of the coefficients for all ITS fits.

To better characterize the contribution of each community to the exchange of peer support among users in recovery, we perform a comparative analysis across communities. We compare the average daily quantity of social dimensions expressed by a recovering author and by the Reddit users interacting with them, on three different subreddit types: (i) `r/OpiatesRecovery`, the main object of this study; (ii) `r/opiates`, the most important subreddit predominantly focused on non-medical use of opioids; (iii) the aggregate of all the other subreddits. These measures reflect the typical share of posts in which a given social dimension is expressed, in a day, on the specific subreddits by the average recovering author or by the respective community.

Figure 5.3c and Figure 5.5 show the bivariate distributions relative to the three communities at study, as kernel density plots together with the marginal distributions for authors and interacting community. While the distribution of the average *Support*, *Trust*, *Status*, and *Similarity* exchanged on `r/opiates` and on other subreddits overlap, the distributions relative to `r/OpiatesRecovery` are mostly non-overlapping with the other communities. Moreover, the recovery-oriented subreddits clearly display a more substantial exchange of these social dimensions. For example, the average author of `r/OpiatesRecovery` shares, on an average day, 55.3% of posts containing a *Support* message and receives a similar one at about the same rate (46.8%). The typical user on `r/opiates`, instead, shares and receives on average less than half of the messages expressing *Support* (22.4% and 20.6%, respectively).

Figure 5.5 shows that the exchanges of *Power* and *Knowledge* also follow different distributions on `r/OpiatesRecovery` w.r.t. the other subreddits (albeit to a lesser extent). At the same time, on the remaining social dimensions, the recovery community is similar to the other communities. These results indicate that, indeed, the `r/OpiatesRecovery` community stands out for its peer support characteristics, contrary to the other main community of discussion for opioids and the general Reddit environment.

With the three analyses described in this section, we empirically show that the `r/OpiatesRecovery` community shares some critical traits with peer support groups. Among the social dimensions found in the messages of the subreddit, *Similarity* resonates with the peer nature of the group: as expressed by Mead, Hilton, and Curtis (2001), a peer support group "is about understanding another's situation emphatically through the shared experience of emotional and psychological pain." In addition, users exchange *Support*, which conveys emotional, social, or practical help. Social Support is the existence of positive psycho-social interactions with others with whom there is mutual *Trust* and concern (Sarason et al., 1983). Moreover, one of the key goals of a peer support group is to provide community reinforcement and

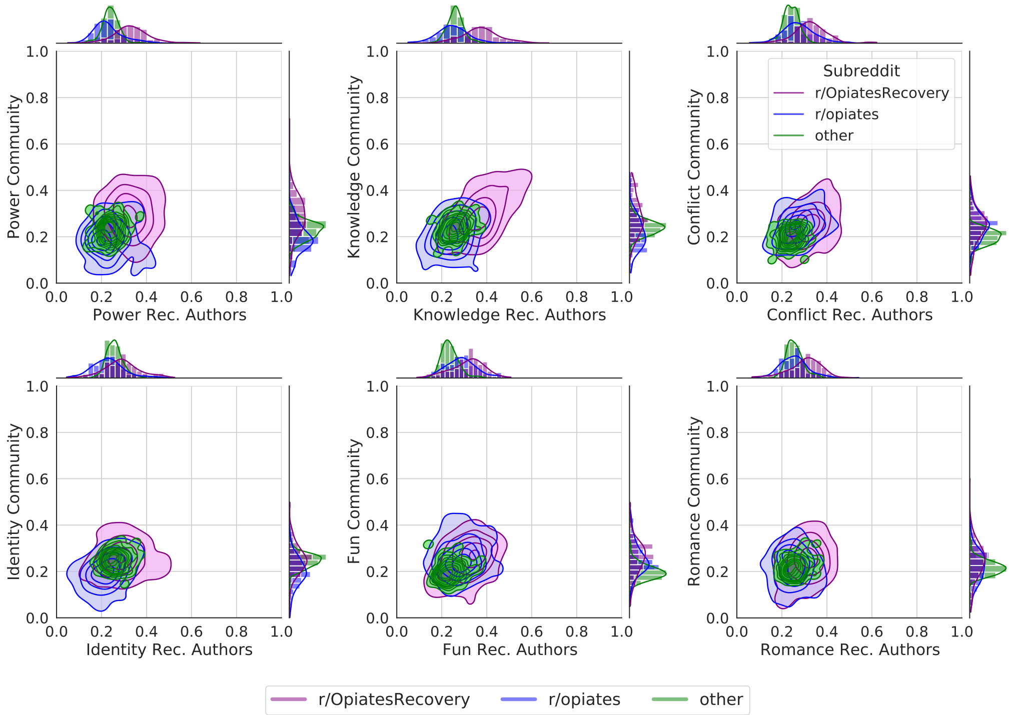


FIGURE 5.5: Daily averages of the share of authors' and community's posts containing a certain social dimensions. In the center, the plots report the bivariate distributions relative to `r/OpiatesRecovery`, `r/opiates` and all the other subreddits combines, shown as kernel density plots, with the marginal authors' and community's distributions on the axes.

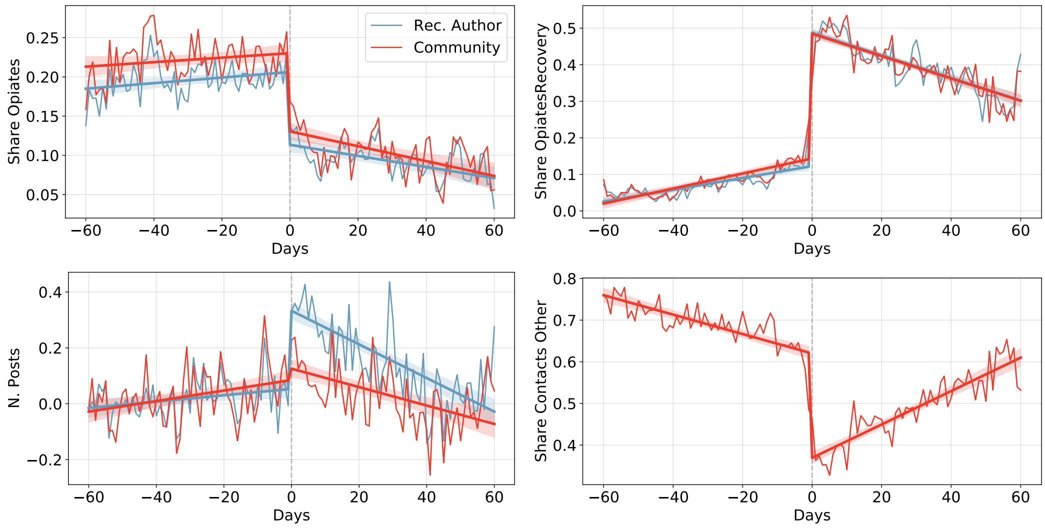
empowerment and to foster self-esteem in participants (Reif et al., 2014), which resonates with our finding of *Status* and *Power* exchanges.

5.4.4 Community shift and social feedback

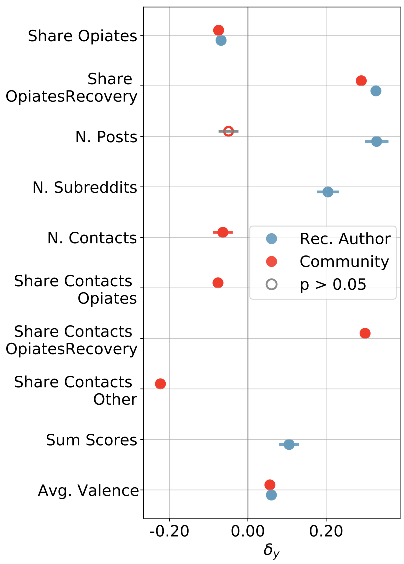
Next, we study the behavior of the recovering authors by evaluating the metrics of behavior based on the posting activity of the recovering authors, defined in Table 5.3.

The results regarding the average behavioral shift and the ITS analysis in Figure 5.6 and Figure 5.7 coherently bring evidence of increased social activity on the platform, of the presence of social feedback, and social group change, with authors shifting interactions from the opioid-using community towards the recovery one.

Figure 5.6b shows the average difference δ_y of all the activity measures y relative to the periods after and before the start of recovery. We find a significant decrease in the share of Reddit posts created by the recovering authors on `r/opiates` (*Share Opiates*) with a simultaneous positive shift in those exchanged on `r/OpiatesRecovery` (*Share OpiatesRecovery*). This migration of authors from the opioid-use community to the recovery-oriented community indicates social group change, a crucial component of the process of social identity change that is part of the recovery process (Best et al., 2016; Haslam et al., 2016). Despite the positive increase in the number of posts created on average by the recovering authors (*N. Posts*) and in the number of subreddits used (*N. Subreddits*) after beginning recovery, we measure a significant decrease in *N. Contacts*, the size of the social group that engages with the posts of the recovering author. Moreover, we observe that after a shift at t_0 away from non-opioid-related subreddits (and towards `r/OpiatesRecovery`), recovering authors steadily increase



(A)



(B)

FIGURE 5.6: Interrupted time series (a)and Average behavioral shift (b) of the activity dimensions regarding the recovering authors and community, respectively reported in blue and red. In panel (a), the thin lines report the daily average of the studied social dimensions, in a temporal span ranging from two months before to two months after the start of detox t_0. The thick lines represent the corresponding ITS fits, with 95% confidence intervals as shaded areas. In panel (b) dots correspond to the average value $\bar{\delta_y}$ and bars report the Standard Error of the Mean (SEM). Values not statistically significant ($P \geq 0.05$) are indicated with hollow markers and gray bars.

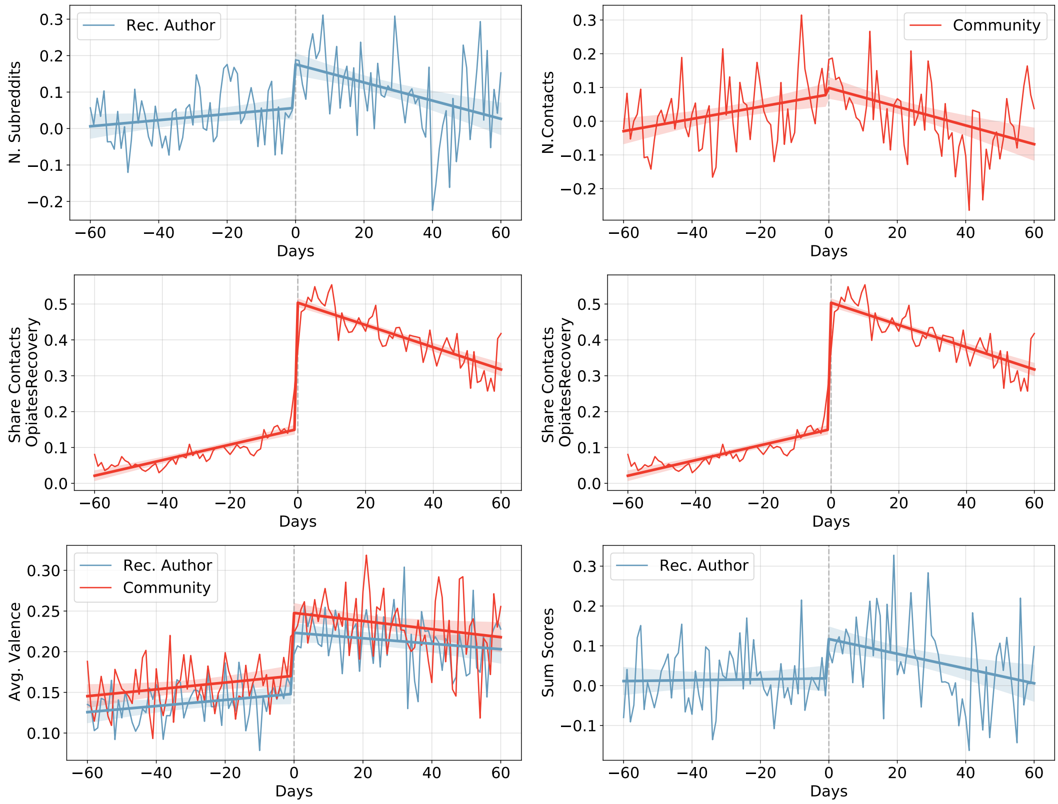


FIGURE 5.7: Interrupted time series of the activity dimensions regarding the authors and community, respectively reported in azure and red. The thin lines report the daily average of the studied dimensions, in a temporal span ranging from two months before to two months after the start of detox t_0. The thick lines represent the corresponding ITS fits, with 95% confidence intervals as shaded areas.

their engagement with non-opioid communities (*Share Contacts Other*) during the course of their recovery process. Lastly, we measure a significant average increase in the score assigned by the community to the posts of the recovering authors (*Sum Scores*) and in the sentiment (*Average Valence*) of the posts exchanged with the community. These measures indicate that during recovery, positive social feedback dynamics occur between recovering authors and their community . The ITS plots in Figure 5.6a show that the average number of posts on Reddit (*N. Posts*) measures a significant positive increase at t_0 and decreases as the recovery progresses. Meanwhile, the participation in `r/opiates` follows an opposite temporal evolution compared to `r/OpiatesRecovery`. The daily share of posts on `r/opiates` is steady up to the beginning of the recovery, when it drastically reduces to half of the previous participation, with further progressive reduction as the recovery advances. Conversely, the participation in the recovery-oriented subreddit (*Share OpiatesRecovery*) grows steadily before the start of detox, and at t_0 its prevalence increases 5-fold, reaching on average more than 40% of the total amount of recovering authors' posts on Reddit. With the progression of the recovery, participation in this subreddit tapers off in favor of other subreddits while still maintaining a considerable share of activity of around 30% after two months. Lastly, the figure shows that the interactions with users on subreddits other than `r/opiates` and `r/OpiatesRecovery` (*Share Contacts Other*), progressively increase during recovery after a decreasing trend before it and a significant reduction at t_0, This result indicates that the authors who persevere

in recovery interact more and more with users of other communities after an initial shrinkage of interactions not tied to opioid consumption/recovery.
The bottom panels in Figure 5.7 show the evolution of two proxy measures of social feedback, *Sum Scores* and *Avg. Valence*: we measure a significant immediate increase at t_0 in both the score assigned by the community to the posts of the recovering authors and in the valence of the comments received or created (*Avg. Valence*). During recovery, the scores assigned to the authors' posts go back on average to pre-recovery levels. The average valence of the comments received by the users is consistently higher than the valence expressed by their submissions, and it remains stable. These findings suggest that the Reddit `r/OpiatesRecovery` community is very prompt at giving positive feedback to the users who begin recovery. Moreover, a new, more positive state is sustained on average by the users in recovery. Table 5.6 in Supplementary reports the values and the statistical significance of the coefficients of the ITS fits. The results of this section, together with those of section 5.4.3 indicate that peer support characteristics of the `r/OpiatesRecovery` community attract those users who are in pursuit of help with their recovery. This need drives the shift in personal and collective observed in our results, which is indeed centered around the start of the recovery. From that day, the recovering authors experience one of the known beneficial aspects of peer support treatment, social group change, shifting away from communities discussing recreational usage of opioids. Moreover, we find that these users start changing their online behavior even before recovery. In particular, they slightly increase their participation in the recovery subreddit, possibly to gather information on this community's fitness to respond to their support needs. Our results also show that the authors who undertake recovery significantly increase their social activities, measured as their engagement on the platform, but decrease the size of the social group they interact with. Further analysis on the community in which these interactions take place unveils that such a decrease is due primarily to lower interactions with users participating in `r/opiates` and other subreddits. On the contrary, the interactions with users in `r/OpiatesRecovery` increase drastically at the beginning of the recovery. These results corroborate the hypothesis on social group change as a recovery constituent. Users lose ties with some of their past and possibly detrimental relationships while opening ties with a restricted but focused group of people in recovery. Finally, it is interesting to notice that the interactions with users on topics that are not opioid-related regain relative importance during the progression of recovery. This means that the users in more advanced stages of recovery also succeed in opening relationships that are no longer related to opioids.

		Author		Community	
		δ_y	SEM	δ_y	SEM
Activity Dimensions	Share Opiates	-0068^{***}	(0.008)	-0075^{***}	(0.009)
	Share OpiatesRecovery	0.327^{***}	(0.012)	0.290^{***}	(0.013)
	N. Posts	0.329^{***}	(0.030)	-0049	(0.025)
	N. Subreddits	0.205^{***}	(0.028)	—	
	N. Contacts	—		-0064^{*}	(0.025)
	Share contacts Opiates	—		-0076^{***}	(0.009)
	Share contacts OpiatesRecovery	—		0.300^{***}	(0.013)
	Share Contacts Other	—		-0223^{***}	(0.013)
	Sum Scores	0.105^{***}	(0.025)	—	
	Avg. Valence	0.060^{***}	(0.011)	0.056^{***}	(0.011)
Social Dimensions	Support	$0.08\ ^{***}$	(0.010)	0.095^{***}	(0.011)
	Trust	0.048^{***}	(0.009)	0.040^{***}	(0.010)
	Status	0.039^{***}	(0.009)	0.059^{***}	(0.010)
	Similarity	0.035^{***}	(0.010)	0.021^{*}	(0.010)
	Fun	0.029^{**}	(0.009)	0.024^{**}	(0.009)
	Conflict	0.020^{*}	(0.009)	0.0	(0.009)
	Knowledge	0.015	(0.010)	-0010	(0.010)
	Power	0.010	(0.009)	0.031^{**}	(0.010)
	Romance	0.002	(0.009)	0.012	(0.009)
	Identity	-0005	(0.009)	0.009	(0.010)

TABLE 5.4: Average Behavioral shift and Standard Error of the Mean.
Significance *: $P <= .05$, **: $P <= .01$, ***: $P <= .001$

		β_0	β_1	β_2	β_3
Author	Support	0.229***	0.001***	0.149***	−0003***
	Trust	0.232***	0.001***	0.085***	−0002***
	Status	0.248***	0.001***	0.095***	−0002***
	Similarity	0.253***	0.001***	0.068***	−0001***
	Fun	0.254***	0.0 *	0.051***	−0001***
	Conflict	0.237***	0.0	0.032***	−0001*
	Knowledge	0.249***	0.0 **	0.037***	−0001***
	Power	0.246***	0.0 *	0.026***	−00
	Romance	0.272***	0.0	0.019**	−00
	Identity	0.232***	0.0	0.014	0.0 *
Community	Support	0.216***	0.001***	0.124***	−0003***
	Trust	0.228***	0.001***	0.076***	−0002***
	Status	0.222***	0.001***	0.086***	−0001*
	Similarity	0.217***	0.0	0.038***	−00 *
	Fun	0.211***	0.0	0.038***	−00
	Conflict	0.227***	0.0	−0003	−0001**
	Knowledge	0.258***	0.0 *	0.012	−0001***
	Power	0.244***	0.0 **	0.051***	−0002***
	Romance	0.216***	0.0	0.029***	−00
	Identity	0.245***	0.0	0.006	−00

TABLE 5.5: Coefficients of ITS analysis of Social features. Coefficient β_0 represents the pre-recovery level; β_1 is its trend approaching the start of recovery; β_2 quantifies the immediate effect attributed to the start of recovery; β_3 trend during recovery. Asterisks indicate significance levels as follows: * $P \leq 0.05$, **: $P \leq 0.01$, ***: $P \leq 0.001$.

		β_0	β_1	β_2	β_3
Author	Share Opiates	0.206***	0.0 *	−0093***	−0001***
	Share OpiatesRecovery	0.122***	0.002***	0.365***	−0005***
	N. Posts	0.053***	0.001*	0.28 ***	−0007***
	N. Subreddits	0.057***	0.001	0.12 ***	−0003***
	Sum Scores	0.018	0.0	0.099***	−0002**
	Avg. Valence	0.148***	0.0 *	0.075***	−0001*
Community	Share Opiates	0.23 ***	0.0	−0100***	−0001***
	Share OpiatesRecovery	0.143***	0.002***	0.341***	−0005***
	N. Posts	0.085***	0.002***	0.041	−0005***
	N. Contacts	0.079***	0.002***	0.019	−0005***
	Share Contacts Opiates	0.229***	0.0	−0102***	−0001***
	Share Contacts OpiatesRecovery	0.151***	0.002***	0.352***	−0005***
	Share Contacts Other	0.62 ***	−0002***	−025 ***	0.006***
	Avg. Valence	0.17 ***	0.0 *	0.077***	−0001**

TABLE 5.6: Coefficients of ITS analysis of activity features. Coefficient β_0 represents the pre-recovery level; β_1 is its trend approaching the start of recovery; β_2 quantifies the immediate effect attributed to the start of recovery; β_3 trend during recovery. Asterisks indicate significance levels as follows: * $P \leq 0.05$, **: $P \leq 0.01$, ***: $P \leq 0.001$.

5.5 Sustained engagement to the recovery community

Lastly, we investigate how social relationships on `r/OpiatesRecovery` impact authors' engagement in the recovery community, which we consider a proxy of commitment to recovery.

With the framework described in Section 5.3, we can estimate the start of recovery, but we can not temporally quantify its outcome in terms of the success of recovery. For this reason, to study the role of peer support on recovery, we choose the weekly participation to `r/OpiatesRecovery` as a proxy of attachment to the community and possibly of progress in recovery. Thus, we compute a binary variable indicating the presence of either submissions or comments on `r/OpiatesRecovery` for each user on a said week. Then, we set up different linear regression tasks for binary classification, using the most relevant social dimensions of conversation exchanged on `r/opiatesrecovery` by each user at week t as covariates to predict the presence of activity of the same user during the next week $t+1$. The three different classification tasks consider as covariates, either the social dimensions expressed by the authors, those expressed by the community, or both. In order to account for different behavior in different stages of progression in recovery, we include the week of prediction t as an independent variable in all the regression scenarios.

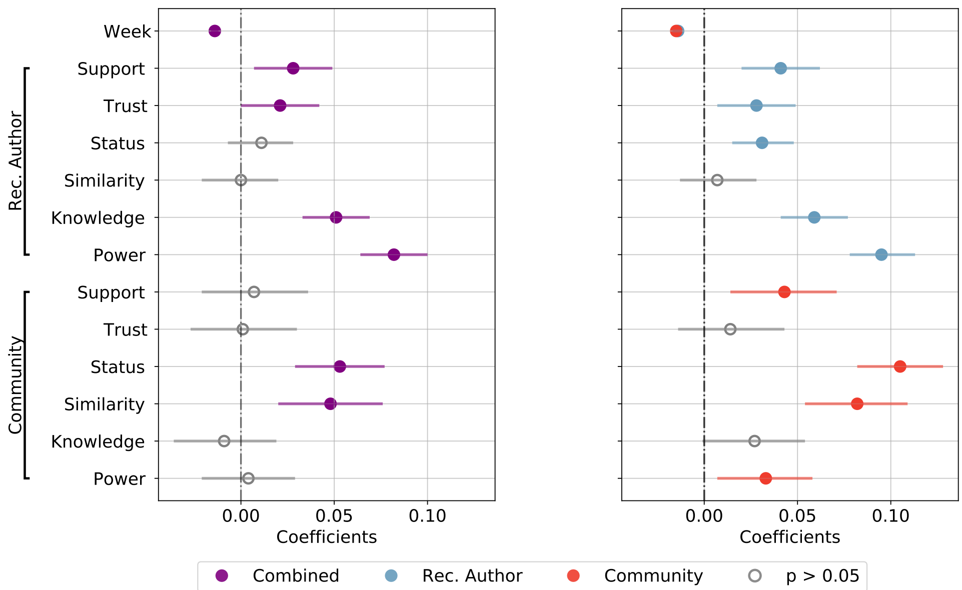


FIGURE 5.8: Coefficients and 95% confidence interval of the binary regression tasks predicting authors' participation in `r/OpiatesRecovery` on the next available week. Values not statistically significant ($P \geq 0.05$) are indicated with hollow markers and gray bars. The colors represent the coefficients of three different models, which use as covariates the combination of all the social dimensions (purple) or just the ones evaluated on Authors' posts (blue) or Community posts (red).

The panels in Figure 5.8 show the coefficients of the binary regression tasks predicting the participation of the authors to `r/OpiatesRecovery` during the next week, based on the set of social dimensions exchanged on the subreddit in the current week. The panels in the figure show the regression coefficients for three different models that consider as covariates: the social dimensions evaluated on posts of the recovering authors (blue), the ones of community posts (red), or the two combined (purple). The models considering the features expressed by the authors (purple and blue models) show that *Power*, *Knowledge*, and *Support* are the social dimensions that contribute most to community attachment among those expressed by the recovering authors. Considering the social dimensions expressed by the community (purple and red models), we find slightly different results regarding the contribution of *Support* and *Power*. Nevertheless, these models indicate that *Status* and *Similarity* dimensions expressed by the community are the most influential community counterparts to the *Power* and *Support* expressed by the authors. These results also confirm that acknowledgment and the presence of peers are important factors in community attachment: the first is shown as the well-known *Power-Status* dynamic among users in recovery, and the second is measured by high *Similarity* exchange. The presence of these social dimensions is not only a defining factor of this community, but it actually is what contributes the most in keeping its users engaged in sharing their recovery journey. The values of the coefficients of the models are reported in **??**. For robustness, we also account for a scenario in which the authors have inhomogeneous Reddit usage, and we set up three additional classification tasks to predict the presence of activity on `r/opiatesRecovery` at the next-available week, i.e., the next week in which the author is active on any subreddit on Reddit. The results of this other task are coherent with those of the next-week prediction task.

The results of this section highlight that sustaining engagement with the recovery community requires great efforts both to the individuals and the community. The recovering authors have to be very active in their participation in this community, particularly in asking for practical and emotional support and sharing their achievements. On the other hand, the community counterparts must be ready to validate the achievements shared and provide the emotional and experiential support needed.

		Combined		Author		Community	
		β	95% CI	β	95% CI	β	95% CI
	Week	-0.014^{***}	(-0.016,-0.012)	-0.014^{***}	(-0.017,-0.012)	-0.015^{***}	(-0.017,-0.012)
Author	Support	0.028^{*}	(0.007,0.049)	0.041^{***}	(0.02,0.062)		-
	Knowledge	0.051^{***}	(0.033,0.069)	0.059^{***}	(0.041,0.077)		-
	Power	0.082^{***}	(0.064,0.1)	0.095^{***}	(0.078,0.113)		-
	Similarity	-0.0	(-0.021,0.02)	0.007	(-0.013,0.028)		-
	Status	0.011	(-0.007,0.028)	0.031^{***}	(0.015,0.048)		-
	Trust	0.021^{*}	(0.0,0.042)	0.028^{**}	(0.007,0.049)		-
Community	Support	0.007	(-0.021,0.036)		-	0.043^{**}	(0.014,0.071)
	Knowledge	-0.009	(-0.036,0.019)		-	0.027	(-0.001,0.054)
	Power	0.004	(-0.021,0.029)		-	0.033^{*}	(0.007,0.058)
	Similarity	0.048^{***}	(0.02,0.076)		-	0.082^{***}	(0.054,0.109)
	Status	0.053^{***}	(0.029,0.077)		-	0.105^{***}	(0.082,0.128)
	Trust	0.001	(-0.027,0.03)		-	0.014	(-0.014,0.043)
	Adj. R^2	0.201		0.195		0.173	
	AIC	1.103e+04		1.110e+04		1.136e+04	
	BIC	1.113e+04		1.115e+04		1.141e+04	

TABLE 5.7: Coefficients of the Next week participation regression task. The columns show the value of the regression coefficients, theirs significance coded as *: $P \leq .05$, **: $P \leq .01$, ***: $P \leq .001$, and the % confidence intervals.

5.6 Conclusions

Our analysis empirically showed that the `r/OpiatesRecovery` community shares some critical traits with peer support groups. As opposed to what happens in other subreddits, we found that the behavior of this community is centered around asking and providing peer support. These peculiar characteristics attract the users who intend to recover and pursue practical and emotional support, providing them with a new community to share their experience with and fostering the abandonment of previous relationships based on the consumption of opioids.

While `r/OpiatesRecovery` shares many traits with traditional peer support groups, it also presents some key differences. The main one is lower friction in moving inside and outside the community, a double-edged sword. Barriers to traditional peer support group participation involve accessibility and personal factors, including time conflicts, difficulties sharing feelings in person, privacy concerns, social stigma, and not being familiar with anyone who is a group member (Rapp et al., 2006; Biegel and Song, 1995). Many of these issues are potentially solved by the opportunity of consulting a peer support group. For instance, the modality of access of online peer support groups –written and asynchronous– differs from in-person ones and allows users to access its content at any time.Thanks to its lower barrier of entry, lack of stigma, and the reassuring presence of peers, the `r/OpiatesRecovery` community offers easy access to support groups, thus possibly reducing the attrition to begin recovery. The online and pseudonymous nature of Reddit may ease the participation of all those who would otherwise suffer social stigma from their social circle (family, colleagues, and acquaintances) due to public admission of OUD. Moreover, physical restrictions might hinder access to peer support groups, while online groups offer a ubiquitous alternative to participate in a community with similar characteristics. The recent Covid-19 pandemic has exacerbated this issue by limiting mobility and discouraging group gatherings (Galanter, White, and Hunter, 2021; Blanco, Compton, and Volkow, 2021), so online alternatives are helping both those who live in secluded places, far from in-person peer support groups, or with mobility restrictions. Conversely, the impersonal nature of online peer support groups clearly limits their efficacy. Of course, in-person meetings foster deeper relationships among peers, where participants are fully engaged and completely focused. The flip side of oprecovery's online and pseudonymous nature is lower accountability and an easier opt-out. The lack of accountability towards one's social circle may thwart the motivation needed to overcome obstacles in the recovery process. Finally, while in-person group meetings encourage regular participation and commitment, which helps the recovery process, online peer support groups do not.

However, despite their differences, the same well-known main driver of traditional peer support, user engagement, was also found in this online alternative. Our results showed that the active commitment of the recovering authors to beginning recovery and their participation in `r/OpiatesRecovery` enables the community to support them. We empirically saw that the shift in behavior and community support is in sync with the actual beginning of recovery, even when its declaration comes after. Moreover, our analysis showed that personal engagement in sharing *Knowledge* and *Power* content contributes significantly to the prolonged participation of the Recovering Authors with the recovery community.

Among the limitations of this work, we must acknowledge that the recovering authors selected in our study are not clinically diagnosed with opioid use disorder. In addition to this, it is possible that some of the users may have employed different usernames, hence some of the meausers performed might suffer of overcounting or undercounting the actual number of unique users. In this chapter, moreover, we did not investigate the role of peer recovery coaches, which cover a crucial role of leading the discussion in many peer support groups. Future work will focus on addressing these two aspects.

In conclusion, in this chapter, we showed that the `r/OpiatesRecovery` subreddit displays similar characteristics to a peer support group and some differences. We highlighted that the presence of such an online community offers the possibility of receiving peer support to Reddit users who are recovering, even in circumstances in which traditional peer support services can not be delivered. Thanks to its peculiar characteristics, we believe that the `r/OpiatesRecovery` should be considered a complementary treatment service. If properly advertised, the availability of highly supportive and informative content about opioid use recovery might spur and give conscience to many of those who face OUD, to those who are in doubt about beginning recovery, and even to those who did not subscribe to Reddit. Taking what we learned about the `r/OpiatesRecovery` community as an example, public health authorities might consider creating or developing similar online-based peer support groups to complement classical treatment and peer recovery services. Moreover, since the authors in this subreddit are in pursuit of peer support, policies could be implemented to spot users in particular need and offer them personalized tools to continue their therapy with more high-effort groups.

Chapter 6

Conclusions

In this dissertation, we took a digital epidemiology approach to address part of the pressing challenges posed by the opioid epidemic in the United States of America. Thanks to advanced computational techniques such as Information Retrieval, Machine Learning, and Natural Language Processing, we collected and analyzed the digital breadcrumbs left by thousands of users on Reddit to provide a novel quantitative perspective on different aspects of the opioid epidemic. Our findings integrate well with the current knowledge and wisdom on many aspects of this health and social crisis and expand each of them, providing both in-depth and at-scale insights. Furthermore, with this work, we proposed a set of novel techniques to acquire and analyze relevant information from digital data on multiple domains.

We contributed to the field of *Public health monitoring* by algorithmically identifying and geolocating a digital cohort of thousands of Reddit users interested in opioid consumption. We provided, as a result, a novel indicator of interest-in-opioids at the US State level that encodes proxy information not entirely grasped by legacy health surveillance methods. We also presented the scientific community with an information retrieval algorithm suitable for identifying relevant subspaces of discussion in an un-indexed social media and a methodology to geolocate users on Reddit based on metadata and self-reporting. Our results show that, if adequately treated, the wealth of data on Reddit may constitute a valuable resource for gathering relevant public health indicators in an undirected and unsolicited way.

By leveraging the discourse on firsthand opioid use on Reddit, we expanded the current research on *Pharmacovigilance* bringing evidence of complex patterns of opioid consumption that include how the drugs are tampered with and administered in a nonmedical context. Our results show the cross-sectional evolution of the adoption of opioid substances and routes of administration spanning several years, valid for spotting users' preferences and potentially dangerous emerging trends of substance consumption. Moreover, we provided a measure of the strength of association between the adoption of opioid substances, routes of administration, and drug tampering, unveiling the multiple complex behaviors embraced for nonmedical consumption of opioids. We also presented a method based on word embeddings to expand the vocabulary knowledge on a given topic by including relevant slang and colloquial terminology directly inferred from the content. We demonstrated that this vocabulary expansion procedure is of primary importance to perform comprehensive and at-scale analyses of user-generated content on social media platforms. We found alternative slang, colloquial, and nonmedical terms referring to opioid substances, routes of administration, and drug-tampering methods, which we provided to the public as structured vocabularies. These results and methodologies underline that the content of Reddit embeds deep knowledge on nonmedical opioid consumption, as much as on so many other topics, that can be leveraged to perform fine-grained and yet exhaustive analyses.

Lastly, we contributed to the field of *aid to rehabilitation* by investigating the potential of Reddit as an online peer support group. We analyzed the content shared by thousands of Reddit authors during the start of the opioid use recovery, and we characterized their social interactions in a time window ranging from two months before to two months after the start of the recovery, according to ten social dimensions of conversation and relationships. Our results show that a particular recovery-oriented community on Reddit exhibits many social characteristics of in-person peer support groups such as emotional and practical support, acknowledgment, and encouragement. We found that the recovering authors are encouraged by the supportive behavior of this community to change personal behavior, favor recovery-oriented relationships, and abandon the opioid-related community. Our results suggest that thanks to its peculiar characteristics, this particular Reddit community is fit to respond to the needs of those who seek support. Hence, we argue that this community might constitute a valid complementary recovery service or an alternative service for those who cannot access standard ones.

Limitations

We acknowledge some shortcomings and limitations in the presented research. Part of the limitations are shared with other research works in the field of digital epidemiology and due either to the use of digital data. Part of them are due o to the methodological pipelines and the techniques used in this work. Either way, these limitations call for theoretical and practical solutions that should be addressed in future work and highlight many possible research opportunities. Since Reddit does not share any socio-economic and demographic characteristics of its users, in this work we did not stratify the cohorts of our studies balancing along dimensions such as gender, age, educational attainment, or wealth. Moreover, our work suffers from some of the known limits of sampling digital cohorts on social media. In particular, the goodness of the data gathered on social media depends first of all on the access of the population to an internet connection, an issue that may cut out the less wealthy and the most segregated part of the population. Second, the age representativeness of the data might depend on the population's digitalization level. Consequently, estimates on social media may potentially neglect the younger and older parts of the age distribution. Third, the use of social media by the users themselves might have intrinsic biases that exclude particular groups of users based on instruction level, ethnicity, religious belief, or gender. This last issue must be considered even if Reddit, in particular, is a social media platform that aims for the most inclusive and generalist content. All these biases might introduce prejudice in the analyses, and should be proactively mitigated (Ntoutsi et al., 2020). Another limitation, shared by all the research contributions discussed in this dissertation, is that we did not assess any clinical information on the Reddit users considered in our experiments. We included the users in our cohorts based on their engagement in subcommunities focusing on the use of opioids and of recovery from opioid use, assuming that all these users shared firsthand experiences and were involved in the discussions out of their own interest. The first limitation with this approach is that the selected individuals are not clinically diagnosed with Opioid Use Disorder, even if it is likely the case for a part of them. The second limitation is that in the case of the cohorts selected for the studies in Chapter 3 and Chapter 4 we considered the entire user base of the selected subreddits to perform our analyses. We cannot exclude the possibility that in some cases, such users might have been discussing secondhand experiences, asking for information for a friend, or reporting information about something that happened to a relative, for instance. Moreover, some users might simply disseminate general news or discuss on intended medical drug use for pain management.

Another limitation, and important research opportunity, is that we did not yet investigate the personal evolution of the role of experienced users in the subreddits about opioid use and opioid use recovery, nor the influence that these might have on the choices of the others in the community. Specifically, in studying the social interactions among authors in recovery, we did not investigate the role of peer recovery coaches. These individuals, who usually have significant recovery experience or have had a successful remission, cover the crucial function of leading the discussion in many in-person peer support groups.

Perspectives and opportunities

Before being a public health issue, the opioid epidemic is a profoundly human and social issue. As such, it is volatile and it constantly transforms depending on the events and the opportunities offered by the context, e.g., the set of social rules, the historical conditions, the markets. With this work, we proved the validity of using digital data, Reddit in particular, and the digital epidemiology approach to tackling multi-faceted issues at different temporal, spatial, and population aggregation levels. Comprehensively addressing these complex phenomena requires state-of-the-art techniques, up to date with the constantly evolving nature of the phenomenon, and possibly forward-thinking. In this perspective, we believe that the value of the research reported in this dissertation resides not only in the quality and usefulness of the results but also in the approach taken to obtain them and in the set of techniques developed and used. Many of the methodologies we proposed in this work, in fact, are ready to be used for general purposes that go beyond the study of the opioid epidemic and are easily adaptable to be applied to other social media.

The research opportunities that arise from our work are multiple. Methods such as the ones we proposed to geolocate the Reddit population, based on exploiting the content shared by the users on Reddit or based on the belonging of users to specific subreddits, could potentially be used in future work to infer many socio-economic characteristics of the user base of Reddit. The acquired knowledge about these characteristics would enable, for instance, to stratify and calibrate the cohorts used for the studies about the opioid epidemic. Moreover, the mapping of the socio-economic characteristics of the entire user base of Reddit itself might be helpful to many research purposes that require a controlled and calibrated cohort and go further the study of the opioid epidemic. Moreover focusing on specific portions of the US territory, i.e. big cities or densely popalted counties, to reach a finer granularity of geolocation could be potentially used in studies which require the ability to discriminate between urban, suburban, and rural areas.

Exciting and valuable directions for future work could be followed by applying techniques similar to those we proposed for selecting authors in recovery. For example, by making use of the users' self-reports with machine learning techniques, one could discern the actual clinical condition of the users, such as Opioid Use Disorder, different Substance use disorders, or other clinical or psychophysical health conditions. This would enable, for instance, to filter only firsthand experiences or verified clinical conditions before the enrollment of the users in the digital cohort.

In combination with the techniques we developed to expand the vocabulary knowledge about any given topic, potentially expanding the techniques to n-grams and sequences of words, selecting cohorts with defined clinical conditions would also enable the in-depth investigation of other relevant health aspects. The related health issues relative to opioid consumption that we did not explore in this work might include, for example, the understanding of adverse drug reactions, the assessment of comorbidities, and the estimation of risk of contracting pathologies due to a specific nonmedical drug consumption behavior.

An interesting new research line that could be implemented in the future, based on a combination of the techniques we proposed in this dissertation, would be to track the personal evolution of the role of the individuals who participate in support communities online. In such complex communities, where peer support is the founding constituent, the users' role may evolve from simple participants, subject of the peer support provided by the community, into active participants who support, help, and influence newcomers.Measuring such evolution of roles and understanding their determinants could be potentially valuable in formulating strategies to ease the process itself. Identifying and measuring the role of peer recovery coaches, for instance, should be the subject of future studies to better comprehend the social dynamics in online peer recovery groups. This kind of knowledge could be beneficial, for instance, to understand better how the valuable information about recovery, useful for successful remission, is conveyed to those who need it.

Lastly, we believe our approach is fit to fully explore the potentialities of Reddit for the reduction of social stigma in various settings. Most of the analyses we performed in this work could be extended to study other social phenomena. In particular, our work could be extended to study cases where the use of social media lowers the effect of discrimination and social stigmas, like use disorders relative to drugs, alcohol, tobacco, and other pathologies involving dependencies, e.g., from food, sex, or gambling.

In conclusion, we believe that the digital approach implemented in this work might have an impact on the current way the opioid epidemic is monitored, studied, and tackled. Our large-scale analyses provide results that show that it is possible to timely monitor the state of the crisis without recurring to traditional methods, which involve complex and often tardive data collection. If replicated and expanded by competent health institutions, we hope that our framework and procedures might yield a better public health monitoring system capable of sensing trends and emerging phenomena thanks to continuous monitoring.

We showed that it is possible to reach a high level of detail on pharmacological aspects of nonmedical opioid consumption and behavioral aspects of recovery by leveraging novel digital data and state-of-the-art computational techniques. We hope that our results and approach will inspire public health stakeholders and research institutions on a new way of investigating the issues posed by the opioid epidemic, with studies based on digital data that inform and enrich those performed with legacy methods.

Finally, we hope that our findings on the potentialities of online-based support groups might motivate new efforts in reducing gaps and stigma in recovery services. With the help of the wisdom of these large communities of peer support and the insights on their relationships and health status, we hope that the relevant public health institution will develop new awareness campaigns and more effective protocols to help anyone who desires a better life also leveraging digital platforms.

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