OPIOID MISUSE TO KRATOM USE: EXPLORING A TRANSITION USING THE NATIONAL SURVEY ON DRUG USE AND HEALTH

by

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ABSTRACT

GILLIAN S. MUNOZ. Opioid Misuse to Kratom Use: Exploring a Transition Using the National Survey on Drug Use and Health.

(Under the direction of DR. JANNE GAUB)

Despite kratom's growing popularity in the United States and claims of its link to opioid use, research has yet to fully delineate factors that lead to its use. Recent research has primarily focused on kratom user-profiles and prevalence in the U.S. This current study explores patterns and associations behind kratom use within a nationally representative sample collected by the Substance Abuse and Mental Health Services Administration (SAMHSA). We apply a machine-learning technique to consider the possibility of predicting kratom use among a large sample and whether kratom use plays a role in opioid cessation. The results show that it was not possible to predict kratom use among the general dataset, even when isolating opioid misusers from the general sample. Further, the results show that kratom use did not play a role in opioid cessation. While it was not possible to predict kratom use, notable predictors were highlighted during this study that has not been previously explored. The findings hold important implications for policy and future research related to kratom.

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DEDICATION

I dedicate this work to everyone in my life who supported me through everything I faced throughout obtaining this degree and finishing this thesis. I would not have been successful without you.

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CHAPTER 1: INTRODUCTION

Kratom's rising popularity in Western countries as a novel psychoactive substance has prompted many questions and concerns with respect to the drug's effects. Surveys and observations of kratom users note its appeal to both recreational and instrumental users who seek its perceived therapeutic benefits (Metastasio et al., 2020; Rogers, Smith, Strickland & Epstein, 2021). Emerging in drug culture, synthetic drugs are becoming commonplace for popular recreational drugs. There has been growing concern for certain synthetic variations, such as fentanyl, which has gained traction in the United States' drug market and has been attributed to the overdose epidemic (Jones, Bekheet, Park & Alexander, 2020). Looking for safer alternatives, users have turned to more "natural" highs, such as kratom (Rosenbaum, Carreiro & Babu, 2012). This would not be the first time research has observed a transition to kratom. Due to rising costs of opium in Thailand, many users were unable to continue its use. Looking for solutions to manage withdrawal symptoms, users began transitioning to kratom (Tanguay, 2011). Now, trends of increased kratom use in the U.S. have initiated interest from researchers to explore the drug, its patterns, and effects. The current study reports on the characteristics associated with the onset of kratom use based on data collected by the National Survey on Drugs and Health over the years of 2019-2020.

CHAPTER 2: LITERATURE REVIEW

Background on Kratom

Kratom (scientific name: *Mitragyna speciosa*) is a tree indigenous to Southeast Asia, where its leaves have an extensive history of medicinal use. It is mostly known as "kratom,"[1] but in Southeast Asia it is also referred to as "ketum," "thang," "thom," "biak-biak," "biak," "kakaum," or "krathom." The leaves contain over 50 known alkaloids, including the primary alkaloids mitragynine and 7-hydroxymitragynine which have been established to bind with opioid receptors (Grundmann, 2017; Kerrigan & Basiliere, 2022; Nicewonder, Buros, Veltri, & Grundmann, 2019). Mitragynine is a G-protein-biased partial agonist of the mu opioid receptor, meaning it binds differentially from opioids by excluding the recruitment of the β-arrestin signaling pathway. Thus, research suggests it produces analgesic effects, but its risk of dependency and respiratory depression is less than that of most opioids (Kruegel & Grundmann, 2018; Nicewonder et al., 2019; Siuda, Carr, Rominger, & Violin, 2017). The primary mitragynine alkaloid has been examined in preclinical trials where the results conclude it may have utility as a pain medication (Kruegel & Grundmann, 2018). Traditionally, kratom has been ingested through chewing fresh or dried leaves or brewing it into a tea. However, oil extracts, powder, and tablets are the primary means of administration for Western users. When kratom is used in low doses, it can produce more stimulating effects similar to cocaine, but when taken in higher doses, it produces analgesic effects similar to opioids (Boyer, Babu, Macalino, & Compton, 2007; Jansen & Prast, 1988; Kruegel & Grundmann, 2017; Ward, Rosenbaum, Hernon, McCurdy, & Boyer, 2011). Some reported acute

[1] Kratom is the most common term for the drug and therefore will be the term that is used throughout the paper.

side effects of kratom use include lethargy, vomiting, hypertension, and in some extreme cases, seizures (Veltri & Grundmann, 2021).

Despite kratom's wide-ranging pharmacological literature, including chemical and biologic pharmacology, there is little known about its behavioral pharmacology or its abuse dependency in human subjects. Most laboratory research has been conducted in animals, specifically rats (see Harizal, Mansor, Hasnan, Tharakan, & Abdullah, 2010; Kruegel & Grundmann, 2018). One study conducted by Hemby et al. (2018) examined abuse liability of kratom through morphine self-administration in rat subjects and found it to lower self-administration, suggesting there to be lower abuse liability. To date, the only known pharmacokinetic human trial of kratom use was facilitated by Trakulsrichai and colleagues (2015), which evaluated blood and urine samples of known chronic kratom-users who were administered varying doses of kratom tea. The findings concluded that kratom had linear pharmacokinetics and a long elimination half-life, meaning it has potential to be considered as an opioid substitute for individuals with opioid use disorder (OUD).

Countries such as Malaysia, Poland, and the United Kingdom have taken steps to ban kratom products due to its interaction with opioid receptors and the potential for abuse.[2] Due to the rising concern of the drug's effects, the Drug Enforcement Agency (DEA) issued a statement in 2016 with the intent to schedule kratom, but quickly rescinded it due to a high volume of backlash, including members of Congress, centered around the lack of scientific research on the

[2] Currently, Mitragyna speciosa and/or mitragynine and/or 7-hydroxymitragynine are regulated in several EU States, such as Denmark, Latvia, Poland, Romania, and Sweden. Similarly, the two primary compounds are illegal in Israel. Australia, Malaysia, and Myanmar have criminalized kratom under narcotic law. In Thailand, kratom had been criminally regulated since 1979 but recent legislation has reversed the ban, moving to regulating sales. Lastly, New Zealand has taken steps to control Mitragyna speciosa and mitragynine under its Medicines Amendment Regulations, which made it medicinal use only. More information is available at: https://www.emcdda.europa.eu/publications/drug-profiles/kratom_en.

drug as well as its therapeutic potential (Drug Enforcement Agency, 2016a; Griffin & Webb, 2017). Similarly, the Food and Drug Administration (FDA) publicly asserted its concerns with the safety of kratom use and encouraged the drug to be placed in Schedule I (Food and Drug Administration, 2017). This reversal by the DEA was uncharacteristic as the agency has rarely gone back on an intent to schedule a drug. A review conducted by Griffin and Webb (2017) examined this decision by the DEA. In the case of kratom, the DEA claimed it was harmful and lacked medicinal value, which is a typical route taken when scheduling a drug. Interestingly, Griffin and Webb (2017) found an insignificant percentage of calls to the CDC reporting kratom poisonings as compared to other drugs, which typically influences the DEA's decision to schedule a substance. Additionally, another important point to highlight is that following the announcement of its intent to schedule kratom, several members of the House of Representatives wrote to the current DEA administrator urging the agency to reconsider until more evidence had been collected on if the move was necessary (Wing, 2016).

Through internet surveys, kratom users have indicated their concerns surrounding the negative effects of banning the drug, such as more individuals turning to other more serious drugs if it were to become unavailable (Prozialeck et al., 2019). In a recent national survey of drug use in the United States, it was estimated that more than 1.7 million individuals were using kratom in the past year (National Survey on Drug Use and Health, 2021). Despite the controversy, kratom remains federally legal in the U.S. and can be legally purchased through online shops, smoke shops, and convenience stores. However, five U.S. states[3] have placed the drug in Schedule I due to health concerns and reported deaths by the CDC, effectively banning it from being sold or

[3] Alabama, Arkansas, Indiana, Rhode Island, and Wisconsin.

distributed, with several other states pushing legislation to control the substance (American Kratom Association, 2022; Eastlack, Cornett & Kaye, 2020).

Kratom Use Motivations and Prevalence

Typically, kratom is used for several reasons. In Southeast Asia, kratom has been used for centuries to treat a variety of ailments through chewing kratom leaves or brewing it into a tea. Other uses include producing stimulating effects to endure long hours of work and to help manage opioid withdrawal (Kruegel & Grundmann, 2018). Southeast Asian users often reflect a predominantly male user profile. In some districts in southern Thailand, kratom use through chewing leaves has been tradition for centuries, with up to 70% of the male population using it daily (Tanguay, 2011). Similar studies surveying kratom users in Malaysia have also seen majority-male respondents, suggesting most users tend to be male (see Ahmad & Aziz, 2012; Singh et al., 2020). Further, these respondents tended to be younger to middle-aged adults, employed, educated, and married. The main route of consumption is typically through chewing fresh leaves or swallowing powdered fresh leaves (Tanguay, 2011). In more recent years, users in southern Thailand have begun making cocktail concoctions referred to as “4x100,” which mimic the effects of alcoholic beverages (EMCDDA). One of the main ingredients includes kratom leaves, along with other substances such as codeine.

The prevalence of kratom use in the 2020 National Survey on Drug Use and Health (NSDUH) was 0.8%, suggesting that 2.1 million people in the United States used kratom in the past year. Kratom use was more prevalent in adults between the ages of 18-25 (0.9%), as well as adults over 26 years of age (0.8%). Recent research utilizing the NSDUH have focused on the prevalence of kratom use and co-occurring substance use disorders as the opioid crisis continues to be an important discussion in the U.S. In a study facilitated by Xu et al. (2021), it was found that there was a 0.5% OUD prevalence in non-kratom users, but this increased "18-fold" to 8.9% among lifetime kratom users. This further confirms the link between opioid use or misuse and kratom use, particularly in the United States. Recently, there have been over 3,000 calls related to kratom exposure to poison control from the years 2014-2019 (Graves et al., 2021). According to a Center for Disease Control (CDC) report in 2021, seven reported deaths were attributed to kratom, with the drug being the only substance in the decedent's system (CDC, 2021). However, it remains unclear if kratom use was the primary cause of death due to many decedents with kratom in the toxicology reports having histories of drug misuse and other health complications.

In the United States, the results of several exploratory surveys on kratom use and motivations suggest its primary uses include chronic pain relief, mood improvement, anxiety reduction, and opioid withdrawal management (Boyer et al., 2007; Coe, Pillitteri, Sembower, Gerlach, & Henningfield, 2019; Garcia-Romeu, Cox, Smith, Dunn, & Griffiths, 2020; Swogger et al., 2015; Ward et al., 2011). In recent U.S. surveys, kratom users often reflect similar Southeast Asian user demographics, with respondents indicating they were young to middle-aged adult males who are fairly educated, married, and employed (Coe et al., 2019; Covey, Vogey, Peckham, & Evoy, 2020; Garcia-Romeu et al., 2020; Palamar, 2021). Differing from the Southeast Asian users, U.S. users tend to prefer consuming kratom through powders or capsules that can be purchased via the Internet or in head shops (Coe et al., 2019). Additionally, kratom users in the United States are often white non-Hispanic males. In fact, some research has stated there may be a strong "white middle-class suburban" user profile in the United States (Rogers, Smith, Strickland, & Epstein, 2021, p. 1). Further, one of the very few studies investigating kratom use in college students found that kratom use tended to be associated with white males or nonconforming individuals (Parent, Woznicki, & Yang, 2022). When asked about their sexual identification, most respondents identified as a sexual minority, which is not typically reported in kratom user research.

Kratom prevalence in Europe or other developed countries is less clear. Most information on use come from case reports, however data suggests that kratom sales have increased over recent years similar to the United States (Smith, Rogers & Strickland, 2021; World Health Organization, 2021). The trade of kratom in Europe and Australia began to emerge in the 21st century, largely due to the accessibility of information regarding the drug on the Internet (Bergen-Cico, MacClurg & Preedy, 2016). Additionally, global marketing of kratom became more common. Like the United States, common routes of administration are through powders taken as capsules or tablets to treat opioid withdrawal symptoms and/or as a substitute for opioids, as well as to self-medicate for pain-related issues (Singh et al., 2016; WHO, 2021).

Previous and current literature has highlighted a strong link between opioid use—particularly opioid *mis*use—and kratom use. Further, research has also maintained similar links between kratom use and use of heroin and/or prescription drugs. Primarily, kratom has been seen to manage withdrawal symptoms, wean users off harder drugs via replacement, and as a means of harm reduction. Research has strongly supported that one of the main purposes of kratom use in recent years is to facilitate harm reduction. This may not come as a surprise as the opioid epidemic has become widespread, and particularly deep-rooted within countries such as the United States. According to a Centers for Disease Control report, there was an estimated 100,306 U.S. deaths. attributed to opioid overdose in 2021 (CDC, 2021). Additionally, new CDC data has shown that the estimate of opioid-related deaths has increased to over 76,600 deaths in 2021, which is almost double what was recorded in the prior year. In relation to harm reduction, a study by Swogger et al. (2015) focused on a qualitative analysis of kratom user experiences, concluding that kratom was often used as a replacement for an unwanted substance. In a similar study, a survey exploring kratom and the mental health motivations of its use showed that 10% of the sample reported using kratom to decrease or desist from an illicit drug they perceived as harmful (Swogger & Walsh, 2018). Most of the evidence-based current information regarding kratom users are primarily collected through online administered assessments. Through the utilization of online surveys, several studies support the link between opioid use and kratom use (see Coe et al., 2019; Grundmann, 2017; Prozialeck et al., 2021; Schimmel et al., 2021; Smith et al., 2021; Smith & Lawson, 2017; Ward et al., 2011). Kratom use has also begun to be discussed in other contexts, such as in sports drug testing and pregnant mothers with babies exhibiting Neonatal Abstinence Syndrome (Elridge, Foster, & Wyble, 2018; Guddat, Görgens, Steinhart, Schänzer, & Thevis, 2016).

However, other research examining the link between opioid use and kratom use motivations has argued there may not be a strong link. One study examining regional kratom use across the United States as it related to opioid-use patterns found insignificant results (Nicewonder et al., 2019). The study found there to be an insignificant response in kratom use to primarily mitigate withdrawal symptoms or fight opioid use on the national, regional, and state level. Further, the study expected there to be high rates of kratom use patterns in states with high opioid misuse rates, which was not supported. Similarly, in a study conducted by Palamar (2021) observing past-year kratom use patterns in the United States, results suggested that opioid use was not associated with increased kratom use. Rather, only individuals who self-reported an opioid use disorder (OUD) had increased kratom use.

Transition to Kratom Use

Nonetheless, a link between opioid use and kratom use exists. What remains unclear are the motivations that ignite the transition from opioids to kratom use, which has yet to be empirically established. Additionally, there is minimal research exploring opioid users and misusers who have abstained from using and how that impacts the onset of kratom use. Prior misusers may be choosing to use kratom to continually desist from using or misusing for reasons that require additional research. However, a transition between the drugs can be speculated based on research conducted in Asia. Dating back to the 1940s when Southeastern Asian countries began placing high taxes on the opium trade, researchers saw a shift in drug use. Specifically, due to rising costs, many opium users began transitioning to kratom to manage withdrawal symptoms (Tanguay, 2011).

In the literature, there are findings that may support the idea of a transition, or rather a transitional period. An online survey given to kratom users found that 6.9% of the respondents had used kratom to reduce or eliminate opioid or heroin use, as well as to relieve their withdrawal symptoms from prior misuse (Coe et al., 2019). When asked about the frequency of opioid use and kratom use during this period, respondents reported significantly less opioid use in the past week and month while using kratom to quit opioids. In a sample of current and former opioid users, it was found that both groups regularly use or used kratom (Singh et al., 2020). However, the motivation behind kratom use differed. Unsurprisingly, current opioid users were using kratom to manage withdrawal symptoms as a replacement method, but former opioid misusers continued to use kratom to induce euphoric-like feelings, which are commonly attributed to the effects of opioids. This could be due to the lower risks attributed with kratom, such as lower dependence risk and lower respiratory depression seen as side effects of opioids. An important motivation for kratom use was highlighted in a study conducted by Smith and Lawson (2017) that surveyed drug misusers in treatment programs. In the sample, 69% of kratom users used the drug to reduce or abstain from opioids or heroin. However, many users indicated their motivation for kratom use was that it was an attractive alternative for passing drug screenings and potentially avoiding a parole violation while still getting similar effects of opioids (Smith & Lawson, 2017). This may explain one of the many reasons for the transition from opioid misuse to kratom use.

Lastly, relevant to the discussion is opioid use and kratom use during the COVID-19 pandemic. Access to pain killers and opioids have significantly decreased in the United States due to the opioid epidemic (Prozialeck et al., 2021), with the lack of access to care further magnified by COVID-19. Metastasio and colleagues (2020) reported that many COVID-19 patients indicated their onset of kratom use was motivated by managing symptoms that are associated with the virus, such as bodily pain, lethargy, and depression. Additionally, it became increasingly difficult for patients to seek care for non-COVID related medical issues, such as chronic pain or substance use disorder (SUD) medication (Prozialeck et al., 2021). Therefore, people began turning to other methods of treatment, such as kratom. While these studies are helpful to initiate the conversation on the transition from opioid use/misuse to kratom use, the literature base would benefit from an analysis on the transition as well as a theoretical discussion providing clarity on the motivations behind it. First, to deepen the existing research concerning kratom use and motivations, a theoretical discussion is necessary.

A Theoretical Approach to Kratom Use: Anomie and General Strain Theory

The term “anomie” derives from the early work of sociologist Emile Durkheim, who established the term to mean the lack of social regulation in modern society. This lack of regulation leads to the promotion of deviant behavior (Durkheim, 1897). Robert Merton’s (1938) theory of social structure and anomie applies this approach by arguing that an integrated society maintains a balance between social structure and approved goals. Further, he argues the balance between these two relates to monetary success. However, when there is a disconnect between these goals and legitimate societal means to achieve them, anomie (or monetary strain) occurs. When an individual is socialized to aspire for monetary success but lacks the means to properly attain those aspirations, anomie then causes strain on the individual or group. Therefore, this strain encourages groups or individuals to take advantage of whatever means necessary to achieve their goals, including illegal behavior. While the theoretical approach focuses anomie on a macro-level, Merton also proposed that individual behavior may also be influenced by the culture and social structure (Merton, 1938; Akers, Sellers, & Jennings, 2021).

Building upon Merton's proposed micro-level approach to anomie—in which strain is produced by the lack of legitimate means to achieve one's goals—Robert Agnew developed a theory that encompassed additional sources of strain besides monetary (Agnew, 1985a). This theory states that "crime and delinquency are an adaptation of stress," where the source of that stress could come from several channels (Akers et al., 2021, p. 204). Agnew suggests three primary types of strain that produce deviant behavior: failure to achieve one's goals, the removal of positive stimuli, and the presentation of negative stimuli to an individual. The failure to achieve one's goals materializes through a few forms, but it can be seen through the traditional lens where the discrepancy between goals and expectations creates a source of strain. However, Agnew's general strain theory expanded to include not only future goals but also immediate goals. Additionally, the theory included blocked opportunities and inadequacies in an individual's abilities or skills which led to their failure (Akers et al., 2021). Further, when an individual experiences extremely traumatic life events, such as the loss of something or someone of great importance, it can produce strain. Lastly, when one is confronted with negative stimuli, such as being exposed to negative experiences involving others, it can produce a source of strain which may lead to deviant behavior.

Connections to Kratom Use

For clarification, the goal of this paper is not to explain kratom use by applying a theoretical approach. However, Agnew's general strain theory may provide a useful perspective to understand the motivations behind prior opioid users transitioning to kratom use, and their continuation to desist from prior misuse. With no current literature reviewing kratom use through theoretical perspectives, there is an opportunity to open the discussion. Thus, for this section, general strain theory is useful in a few ways. In relation to the concept of strain where a discrepancy between one's goals and the legitimate means to achieve them produces strain, one's failure to achieve future and immediate goals is important. For example, depending on an individual's level of misuse of opioids, prescription painkillers, or heroin, there may be several ways they would be blocked from achieving their future or immediate goals. Individuals misusing drugs may experience failure based on blocked opportunities due to their misuse, such as impeded employment opportunities where drug screening may disqualify them for a position. Further, failure due to an individual's inadequacies in their ability to function in proper social and societal settings may produce strain. For example, someone who is experiencing opioid misuse may be unable to participate in everyday activities, such as supporting their spouse or children. It is fair to assume this could create a significant amount of strain. Likewise, a great source of strain may be experienced when the removal of positive stimuli occurs, such as the loss of something or someone of high value. The loss of employment, a spouse, or peers due to drug misuse or the discovery of one's drug misuse can produce feelings of strain. Further, in an expansion of the general strain theory, Agnew proposed new forms of strain, such as anticipated strains, which refers to an individual's consideration of risk or fear of future stressors relating to their behavior (Akers et al., 2021; Stogner & Gibson, 2010). While this concept of strain has minimal literature investigating its influence, it may be useful in exploring the transition of prior opioid misuse to kratom use. This concept may help explain drug misusers experiencing strain due to the evaluation of risk or fear of future stressors related to their misuse. A few examples of future stressors include fear of discovery, inability to quit, losing relationships, and other anticipated scenarios relating to drug misuse.

Considering these sources of strain produced by an individual's drug use or misuse, it may be plausible to assume that these factors may influence one's transition to kratom. Strain can be created when an individual isn't able to reach future or immediate goals due to their opioid, prescription painkiller, or heroin misuse, specifically. Additionally, the loss of positive stimuli, such as the loss of a spouse or employment, may add significant feelings of stress experienced by an individual struggling with misuse. Lastly, individuals may also undergo anticipated strain produced by the risk or fear of future stressors related to their drug misuse, such as fear of discovery, risk of losing one's job, or fear of one's misuse becoming uncontrollable. An individual experiencing these strains may turn to alternative options to remove them, such as options with less associated risk and stress. To drug users and misusers, kratom is an attractive option due to its current legal status in the United States as well as its lower risk of side effects, such as lower risk of respiratory depression and dependency. Further, drug screenings don't currently screen for kratom use which may lessen feelings of stress surrounding an individual's professional goals or future job prospects. For these potential motivations, examining the transition or transitionary period of opioid misuse to kratom use is significant.

Current Study

A meaningful opportunity lies in the lack of research on kratom use, particularly in the United States. Further, it is important to cover the gap in the existing literature exploring the transition from opioid misuse to using kratom. Here, research can begin to explore the potential patterns behind this transition and continue to investigate the behaviors of delinquency, such as drug use. Currently, the literature discusses drug users who use both opioids and kratom, but it hasn't delineated individuals who ceased opioid use and chose an alternative drug, such as kratom, to continue their desistance from deviant behavior. Lastly, research has begun using more advanced statistical models to analyze data in criminal justice, including drug use. This study aims to address the highlighted issues by using data from the NSDUH to facilitate a machine learning analysis. Specifically, the following research questions will be addressed:

1. Can machine learning methods predict kratom use?
2. Are the predictors of kratom use the same when isolating opioid misusers?
3. Is kratom use an important predictor of opioid cessation among individuals who have used opioids?

CHAPTER 3: METHODOLOGY

3.1 Dataset

Data from the 2019-2021 National Survey on Drug Use and Health (NSDUH) – a nationally representative, cross-sectional survey – will be used for this analysis. The data consists of randomly selected households across the United States where one or more residents completed full in-person or online interviews. Households chosen for this survey differ every year. The purpose of the NSDUH is to provide insights into tobacco, alcohol, and drug use, mental health, and other related issues to inform the public, health programs, and related policies.

Starting in the 2019 NSDUH assessment, the issue of kratom use was incorporated into the survey for the first time. In the 2020 and 2021 survey, kratom use was moved under the "Emerging Issues" category, but the two questions posed to respondents remained the same. It is extremely important to note that data collection in 2020 was heavily impacted due to the coronavirus (COVID-19) pandemic. Historically, the NSDUH is conducted through in-person interviews. However, due to the pandemic, in-person data collection was suspended until mid-year of 2020, where small-scale collection efforts were executed in states labeled safe based on the current COVID-19 metrics. Following these efforts, data collection was primarily conducted through web-based interviews with in-person data collection continuing in states and counties considered safe. Given the addition of web-based interviews in the 2020 data collection, differences in response and nonresponse patterns emerged, which led to changes in how the data was processed. Moving into the data collection period for the 2021 NSDUH, data were again collected using web-based interviews and in-person interviews. The difference between 2020 and 20201 is that the 2021 administration implemented the mixed interview method for the entire data collection period as opposed to 2020 which did not. Lastly, the NSDUH data is publicly available, and all identifying information is kept confidential with each respondent having a unique identifier.

3.2. Data Cleaning Process and Final Sample

General Cleaning Procedure

The data used in this study comes from a larger dataset from the NSDUH. Specifically, the data is pulled from three larger datasets provided by the 2019-2021 NSDUH. Due to this study's focus on adult kratom use, it was decided that responses from individuals under the age of 18[4] weren't going to be included. For 2019, the full dataset includes 56,136 observations. After removing individuals under the age of 18 from the dataset, 42,739 observations remained for 2019. In 2020's dataset, the complete file includes 32,894 observations. When individuals under the age of 18 were removed from the dataset, 27,170 observations remained for 2020. Lastly, in 2021, the full dataset includes 58,034 observations. Once respondents under the age of 18 were removed, 47,291 remained for 2021. In total, the primary sample for this study included 117,200 (N=117,200) observations.

Subgroup Cleaning Procedure

For the secondary and tertiary analyses, smaller subgroups were created from the primary sample of 117,200 observations (N=117,200). Specifically, two subgroups were identified and labeled as "opioid misuser subgroup" and "opioid cessation subgroup." For the opioid misuser subgroup, respondents were identified through an opioid use variable (OPINMYR), which was

[4] It was possible to identify the age of respondents through one of the key variables (AGE2, AGE3) which asked individuals to indicate how old they were, with age options beginning with 12 years old up to 65 years or older. Any respondent who chose answer choices of 12 years old to 17 years old were considered young adults or adolescents, and thus were not considered adults in this analysis.

present in all three surveys. This variable was a recode and was done so by pulling individuals who had indicated earlier in the survey whether they misused heroin or pain relievers in the past year. Since the opioid misuser subgroup aims to focus on opioid misusers, the observations that answered “yes” were selected to be in this subgroup. Specifically, 1,954 individuals in 2019 indicated they had misused opioids in the past year, 994 in 2020, and 1,640 individuals in 2021. The final subgroup resulted in 4,588 (N=4,588) observations.

The creation of the opioid cessation subgroup aims to focus on individuals who were identified as ever ***using*** any opioids to create our sample. Since there wasn’t a variable represented in the survey specifically asking if respondents had ever used “opioids” or about “opioid” use recency, we looked to similar variables that could best capture individuals who had ever used opioids. Heroin use and pain reliever use recency were chosen as potential variables to create the opioid cessation subgroup. Starting with the primary sample (N=117,200), we looked at how many observations remained when pulling individuals who had indicated they had ever used heroin compared to how many remained of who identified they had ever used pain relievers. There were 2,671 observations for heroin use recency and 30,544 observations for pain reliever use recency. Looking at individuals who had used heroin and pain relievers, only 818 individuals overlapped. When looking at individuals who had used more than a year ago for both groups, only 294 respondents overlapped. Additionally, if we were looking to use both variables, there are a considerable number of responses for pain reliever use compared to heroin use recency. If we were to include heroin use recency observations, the number of non-users removed would be significantly more due to the lack of responses. With this considered, the sample will be based on the pain reliever use recency variable with the final subgroup sample being 30,544 observations (N=30,544). With our outcome variable now becoming opioid cessation, the classification options will include those who have recently misused pain relievers in the past year and those who have abstained. Non-users won't be included and will be removed in the random forest.

Cleaning up Unnecessary Values and Value Reassignments

Throughout the NSDUH codebook, variables are described along with their values. Most variables have several values, while others are coded as 0/1 (No=0/Yes=1). To improve conciseness and consistency across the samples, variables with multiple values were reassigned when it made sense to do so. For example, for the variable, "BOOKED," respondents were asked if they had ever been arrested and booked for breaking the law. Values consisted of 1=Yes, 2=No, 3=YES Logically Assigned, 85=BAD DATA Logically Assigned, 94= DON'T KNOW, 97=REFUSED, AND 98=BLANK (No Answer). For categorical questions such as this one, the extra values can be reassigned. The respondents who qualified for the value of 3 can be reassigned to 1, which equals "yes." When a value states, "YES Logically Assigned," it means the respondent had responded to an earlier question about being arrested and therefore can be logically assigned to this question. For this analysis, anyone whose value was "YES Logically Assigned," was reassigned to a value of "yes." Those who had the value of 85 assigned to them were assigned "BAD DATA" due to answering differently. For example, in this case, an individual may have indicated in an earlier question they had been arrested and then for this question indicated they had never been arrested before. Therefore, their response is considered "bad data," and was removed by changing its value to equal "NA." For the values 94, 97, and 98, since the respondent's either did not answer, purposefully or not, or stated they did not know, we cannot assign them a value. Thus, their values were changed to "NA" as they do not provide value to this analysis.

Additionally, for frequency variables included in the dataset, some of these reassignments differed slightly. For example, one of the variables captured in the dataset asked individuals how many times they had attended a religious service in the past year. Respondents were able to give a number or range of how frequently they had attended a service. Similar values were seen for this variable, including 94, 97, and 98. The respondents who had answered that they didn't know (94=DON'T KNOW) or left it blank (98=BLANK), were assigned a value of "0," which was an answer choice for those who had not attended any service in the past year. Since it was not a categorical (Yes/No) variable, it can be fair to assume someone who doesn't know may lean toward the answer choice of not attended any service at all in the past year. Overall, this value reassignment process was applied to all qualifying variables chosen for this dataset.

3.3. Variables

This analysis includes several relevant variables. In total, 154 variables were included in this study. It is important to note that Models 1-3 use 153 of the 154 variables. Models 4 and 5 required an additional variable to identify each year.[5] Further, Model 4 used all 154 variables. Model 5 used 152 of the 154 variables; two were removed as they were extremely similar to the outcome variable and would cloud results. Overall, almost all the variables were the same for each analysis.

For Research Questions 1 and 2, the outcome variable (dependent variable) is past year kratom use, which is measured by asking respondents a string of questions. Respondents were first asked if they had ever, even once, used kratom. If they answered yes, they were then asked to indicate how long it had been since they last used. The options included: within the past 30 days, more than 30 days but within in the last 12 months, or more than 12 months ago. Finally, a recoded

[5] Model 1-3 did not require a variable for the year as they were already broken out by year.

past year use variable was constructed to group kratom use as "yes" or "no" by assigning "no" to those who answered no to if they had ever used kratom before as well as those who had used more than a year ago. The value "yes" was assigned to those who indicated they had used kratom within the past year. This recoded past year kratom use will be used as the outcome variable.

The third research question requires a change in the outcome variable since we are looking to test if kratom use is an important variable in predicting opioid cessation. With the outcome variable changing, past year kratom use will become an independent variable. To answer Research Question 3, the outcome variable (dependent variable) will change to pain reliever misuse recency, which is also measured by asking respondents a string of questions. Foremost, pain reliever misuse recency was chosen as the outcome variable due to the lack of variables representing opioid misuse recency within the dataset. Pain reliever misuse was chosen for its similarity, which was confirmed by its inclusion in the past year opioid misuse recode variable.[6] Respondents were asked if they had ever used pain relievers not directed by their doctor using "yes" or "no." If they answered yes, they were then asked to indicate when their most recent pain reliever misuse was. The options included the following: within the past 30 days, more than 30 days but within in the last 12 months, or more than 12 months ago. Lastly, a dichotomous recoded pain reliever misuse recency variable was created to group individuals based on the option chosen. Individuals who indicated they had misused within the past 30 days or those who had misused more than 30 days ago but within 12 months were grouped together to represent those who had misused in the past year. Individuals

[6] The past year opioid misuse variable (OPINMY) was created by pulling individuals who indicated they had used heroin or misused pain relievers in the past year. The variable for misusing pain relievers in the past year was created from a prior question asking respondents about pain reliever misuse recency, which included the options of in the past 30 days, more than 30 days but within 12 months, and more than 12 months ago. This pain reliever misuse recency was decided to be the outcome variable so we could pinpoint who had stopped using and who didn't. Please refer to the Appendix for a breakdown of the variables.

who had indicated they hadn't misused in the past year were coded as such. The purpose of using pain reliever misuse recency for Research Question 3's outcome variable is to have insight into what variables affect whether opioid cessation occurs. Further, due to the machine learning method chosen for this study, various inputs (independent variables) were chosen from the dataset. To pare down the number of inputs for this analysis, research was conducted in the existing literature to pinpoint the most relevant variables. The following subsections attempt to group the inputs chosen into categories where brief descriptions are provided.

Drug Use

Respondents were asked several questions throughout the survey regarding their drug use. (A complete list of variables is included in the Appendix) Inputs were determined in a few ways. Individuals were asked if they had ever used the following drugs (Yes/No): marijuana, cocaine, crack, heroin, peyote, LSD, PCP, ecstasy or molly, ketamine, DMT/AMT/FOXY, hallucinogens, inhalants, methamphetamine, tranquilizer, stimulant, sedative, illicit pain reliever use, illicit tranquilizer use, illicit stimulant use, and illicit sedative use. The response options included: within the past 30 days, more than 30 days ago but within past 12 months and used more than 12 months ago. Additionally, respondents were asked if they had used the drug in the past year (Yes/No) and if they had initiated use in the past year (Yes/No). Drug misuse inputs were constructed by whether an individual indicated they had misused in the past year or did not misuse in the past year. Other ways drug misuse inputs were constructed were by asking respondents if they had used a drug longer than they were prescribed for, for example (Yes/No). Lastly, respondents were questioned on their motivations regarding drug use, such as prompting them to indicate the main reason they used pain relievers. Some of the response options included for pain relief, help with sleep, or to help with their emotions.

Respondents were also asked about their perceptions of certain drugs, such as their perceived difficulty to get a drug or the risk associated with trying it. For example, respondents were asked, "How difficult or easy would it be for you to get some marijuana, if you wanted some?" Respondents were given a few answer choices, such as, "probably impossible," "very difficult," "fairly difficult," "fairly easy," and "very easy." Another example concerning risk of drug use can be seen posed to respondents as how much risk they see harming themselves physically if they were to use heroin once or twice a week. The answer choices included: "no risk," "slight risk," "moderate risk," and "great risk." A similar question was asked respondents how they felt about adults trying marijuana ("Neither Disapprove nor Approve," "Somewhat Disapprove," "Strongly Disapprove").

Criminal History, Drug Penalties, and Drug Testing

The NSDUH included criminal history questions that were used to create crime inputs. Respondents were prompted to indicate if they had been arrested for breaking the law (Yes/No), and whether they had been on parole/supervised release in the past 12 months or had been on probation in the past 12 months (Yes/No). The NSDUH also asked questions regarding drug laws in the respondent's state. For example, one question asked what the maximum penalty was in a respondent's residing state for first-time possession of marijuana. Response options included: a fine, probation, community service, possible prison sentence, or mandatory prison sentence. Additionally, a question about selling drugs was included in the survey which covered if a respondent had ever illegally sold drugs in the past year (Yes/No). Lastly, a few questions inquired about workplace drug/alcohol policies and drug testing. Specifically, individuals were asked if their workplace had a written policy about the use of drugs or alcohol (Yes/No), if their workplace offered assistance related to drugs or alcohol (Yes/No), if their workplace tested for drugs (Yes/No), and if they tested during the hiring process (Yes/No).

Mental Health, Physical Health, and Treatment History

Additionally, respondents were asked questions related to mental health, physical health, and past treatment history. A handful of inputs in this category were determined by various mental health-related questions posed to respondents. Several questions were asked to gauge the respondent's level of impairment regarding their mental health. Likewise, several questions were asked to gauge the respondent's level of psychological distress. Both were constructed into variables where the respondent's total score was associated with this variable. Other inputs related to adult mental health, such as adult depression, was determined by a series of questions on the respondent's mental health.

The NSDUH asked various health-related questions that were included as relevant inputs for this analysis. Individuals were asked if they had ever been diagnosed with the following physical ailments (Yes/No): heart condition, diabetes, COPD, cirrhosis, hepatitis C or B, kidney disease, asthma, cancer, or high blood pressure. Further, an additional question was asked if a respondent said "yes" to ever having cancer concerning if they had cancer in the past year (Yes/No). Female respondents were asked if they were currently pregnant (Yes/No).

Likewise, additional inputs included in this category were determined by individuals indicating whether they had received treatment in the past year for illegal drug use and/or alcohol use (Yes/No). Respondents were also asked if they had received treatment in outpatient facilities (Yes/No) or in-patient facilities (Yes/No) in the past year for mental health. The number of times a respondent had visited the doctor about their health in the past year, visited an outpatient facility in the past year, and the number of times they had been to the hospital in the past year were also included. Ranges were given as response options (i.e., 10-12 times, 13-15 times, etc.). Other types of treatment were gauged through questions regarding if the respondent had sought treatment from alternative sources in the past year, such as herbalists, acupuncturists, or self-help groups. Other treatment-related inputs, such as medication-assisted treatment, were determined by respondents stating whether they had received alcohol or opioid medication-assisted treatment in the past year (Yes/No). More perception-based inputs were also included by respondents indicating whether they had perceived they had ever had an alcohol- or drug-use problem (Yes/No) and if they felt as if they had recovered from the alcohol- or drug-use problem (Yes/No). Additionally, respondents indicated whether they had perceived they had recovered from mental health issues (Yes/No).

Lastly, inputs related to insurance and treatment coverage were administered to respondents. Questions regarding what kind of coverage individuals had to pay for their treatment was included, such as if the respondent had public insurance, private insurance, Medicare, Medicaid, or another type of insurance (Yes/No). An insurance recode variable was constructed to capture overall insurance coverage of all respondents, with "yes" being they were covered by some type of insurance and "no" being they were not covered by any insurance.

Demographics

Key demographic questions were asked of respondents in the NSDUH and will be used as inputs for this analysis. Firstly, military service was captured in the survey by participants indicating "yes" or "no" to if they had ever served in the military. Respondents were also asked several other demographic questions, such as their sexual identification (heterosexual, bisexual, and lesbian or gay), gender (male, female), marital status (married, divorced/separated, widowed, or never been married), age (18-20, 21-23, 24 or 25, 26-29, 30-34, 35-49, 50-64, 65 or older), race (Non-Hispanic White, Non-Hispanic Black/African-American, Non-Hispanic Asian, Non-Hispanic Native American/AK Native, Non-Hispanic Pacific Islander/Native HI, Non-Hispanic more than one race, and Hispanic), education (less than high school, high school graduate, some college/associates, college graduate), overall health (excellent, very good, good, fair/poor), income, and employment status (employed full-time, part-time, unemployed, or other).

Social Environment

Inputs related to an individual's social environment were included. Specifically, inputs regarding social ties to religion and faith-based perceptions. Respondents were asked how frequently they attended a religious service in the past year, which answer options included ranges such as 0 times, 1-2 times, etc. Other questions asked in a Likert-Scale fashion how important their beliefs were to them and if they felt their religious beliefs influenced their decisions ("Strongly Disagree," "Disagree," "Agree," "Strongly Agree").

3.4. Analytic Strategy

While much research exists on the link between opioid use and kratom use, there is no consistent empirical evidence documenting the transition from using opioids to kratom. Similarly, there has been minimal research exploring a variety of potential predictors of kratom use. The goal of this analysis is to assess patterns and associations between the numerous predictor variables and the outcome variable—past-year kratom use—to develop the current literature base. An additional goal of this analysis is to assess if past year kratom use is an important predictor of opioid cessation. A machine learning methodology will be applied to determine if any patterns and associations are present. Certain links to kratom, such as opioid use, have been made in prior research and would be unsurprising. However, if classifications through this method are made with an encouraging degree of accuracy, it may identify predictors of kratom use currently undiscovered to researchers. Additionally, there are no existing studies that use this method to predict kratom use. This analysis may also confirm whether kratom use can, in fact, be predicted.

Specifically, the machine-learning methodology used in this study will be the random forest classification model. The term “random forest,” coined by Breiman (2001a), refers to a bagging procedure that is conducted by taking bootstrap samples from large datasets to construct many trees (Berk, 2008). Bagging or “bootstrap aggregating” is a method described best by Breiman (1996) where it produces several versions of a predictor and then uses those versions to find an aggregated predictor. However, random forest is more than the typical bagging method, whereas each tree is constructed, a random sample of predictors (or features) are chosen before each node is split. This process is then repeated for each node, thus leaving us with many trees produced by a random sample of cases (Berk, 2008). In the final step, classifications are then made by a majority vote of what was produced by the random forest trees.

There are a few important features that establish the random forest model as a good fit for this analysis. Due to the lack of theoretical or empirical guidance to understand what characteristics are associated with predicting kratom use, the random forest method provides a way to uncover unanticipated associations. Thus, the revelation of unanticipated associations would contribute to the development of understanding the onset of kratom use. Additionally, the model is not only flexible, but is suitable for many predictors. Large trees can be extremely effective in that they reduce bias and reduce the risk of overfitting the data, which can be one of the main issues in machine learning. However, there are also limitations to the random forest model. There is the issue of overfitting the training data, which can lead to potentially poor prediction in the test data. Likewise, it could be possible that some of the associations are spurious due to an unobserved variable explaining both variation in an important predictor and the outcome variable.

A random forest classification model will be constructed in RStudio based on the 2019-2021 NSDUH datasets. It is important to keep in mind the differences in data collection between the three surveys due to the coronavirus pandemic – with comparisons between the data being done so with caution. The aim of this study is to uncover potential characteristics associated with kratom use, not to compare 2019-2021 kratom use. Before estimating the model, the dataset will need to be fit to the machine learning algorithm. To begin training the algorithm, a split in the data is necessary to create a training and test set, where 70% of the dataset will be allocated to the training set and 30% will be the test set. There are a few ways to split the data, but for this analysis, the dplyr package in R will be used to separate the dataset into the respective training and test sets. Once the data is split, the training set will be used to train the random forest classifier and the test set will be used to gauge the model's performance. Out-of-bag data—data not chosen during the sampling process—will then be dropped down the tree. The random forest function in R will continue this process numerous times, creating a variety of random forest trees while keeping count of the number of times the observation is classified.

A confusion matrix (or table) will be constructed for forecasting kratom use. The confusion table will simply show whether the random forest model is able to predict with accuracy. The accuracy of the model to classify who uses kratom and who does not based on the predictors will be instrumental in supporting Research Question 1, which addresses whether machine-learning methods can predict kratom use.

Additionally, predictor importance and response function will also be implemented. Predictor importance will highlight certain predictors that showed to be most effective, where response function will provide insight into how each predictor is related to the response variable through partial dependence plots. Berk (2008) best explains that partial dependence plots "show the relationship between a predictor and the response averaged within the joint values of the other predictors as they are represented in a tree." The model's important variable function will provide vital insight into Research Question 2, which is if the important predictors are still the same for kratom use when isolating opioid misusers, while Research Question 3 looks to answer if kratom use is an important predictor of opioid cessation among opioid misusers.

3.5. Test Procedures

Random Forest Models

Once the samples were constructed, five separate random forest models were created and run. For all five models, the out-of-bag (OOB) error estimates on the training set as well as the confusion matrix are reported. These are considered for the models' overall accuracy. The results of the random forest models were interpreted through the Mean Decrease Gini and Mean Decrease Accuracy (Han, Guo, & Yu, 2016). To enhance the predictive power of the random forest classifier model, parameters are typically standard. Some of these parameters include the number of trees the algorithm builds, the max number of features the model considers before splitting its nodes, as well as proximity and importance. Proximities are typically calculated to see the nearness between observations. Importance is used to allow visibility into the most important features found to classify the outcome variable. The number of trees this study's model was told to create were 250 trees, with 12 features being considered at any point in time in the decision trees. Proximity was set to false, due to processing issues with storage. Importance was set to true to compute the important predictors. Lastly, the missing data function, na.omit, was used to drop rows with missing data. Thus, individuals with NA responses would be dropped.

For Research Question 1, a general approach was taken. Due to space constraints and the impact of the pandemic on data collection beginning in the 2020 survey, each year and their respective observations were broken out from the primary sample (N=117,200) and tested separately. The purpose of this was to account for the presence of any major differences between the years. Thus, observations from 2019, 2020, and 2021 were run in their own random forest model. After each random forest model was run, variable importance and partial dependence plot functions were run to determine the important variables in predicting past year kratom use as well as how they are associated to past year kratom use. Partial dependence plots were done for the top five predictors in all three models.

To address Research Question 2, the fourth random forest model was set up and run for the opioid user subgroup (N=4,588). The variable importance function was also run to identify the important predictors of past year kratom use when isolating opioid users from the primary sample. Partial dependence plots were created for the top five important predictors. Similarly, Research Question 3 was addressed by testing the fifth random forest model on the opioid cessation subgroup (N=30,544). Differing from the previous four models, variable importance was conducted to identify the important predictors of opioid cessation when also isolating opioid users from the primary sample. The purpose of this was to see if past year kratom use was indeed an important predictor of opioid cessation, with past year kratom use becoming an input rather than the outcome variable. Lastly, partial dependence plots were constructed for the top five important predictors of opioid cessation.

CHAPTER 4: RESULTS

4.1. Research Question 1: general classification of past year kratom use

In Model 1-3, a random forest was implemented to identify if it was possible to predict past year kratom users out of the NSDUH datasets by several characteristics, such as drug use, drug work policies, mental health, physical health, treatment history, criminal history, demographics, and social environment. The random forest models were trained using the split training sample to predict the past year kratom users, with three separate OOB error rates. Model 1 (2019) had an OOB error rate of 1.11%. A confusion matrix was computed to further review the finding which can be seen in Figure 2.

Model 1 Confusion Matrix

	No Kratom Use in Past Year	Kratom Use in Past Year	Class Error
No Kratom Use in Past Year	14889	0	0
Kratom Use in Past Year	167	0	1

Figure 2. Random Forest Results for Model 1

Model 1 accuracy for the random forest suggested that it was not able to predict past-year kratom users. However, it was extremely accurate in predicting individuals who did not use kratom in the past year. Further, the Mean Decrease Gini (Gini) and Mean Decrease Accuracy (MDA) were used to interpret the results of the random forest. Looking specifically at the Gini and MDA for past-year kratom users, the high-importance variables overlapped slightly. The top high-importance variables for the MDA were the respondent's perception on how difficult it was to obtain marijuana, LSD-use recency, using stimulants not directed by a doctor to get high, age, and cocaine-use recency. The high-importance predictors for the Gini index were the respondent's level of impairment score, the number of times they had visited the doctor in the past year, age, the legal penalty in their state for marijuana possession, and perceived difficulty in obtaining LSD. Lastly, partial dependence plots (PDP) were computed on the top five important variables. PDPs are used to provide insight into how each important predictor is related to the outcome variable. For example, the PDP for past year kratom use and perceived difficulty in obtaining marijuana showed similar effects on the model predictions. This means that there was not a response option for perceived difficulty that was related more to predicting kratom use. Each option had similar effects on the predictions. However, for those who found it "Fairly Difficult" to obtain marijuana, there were fewer predictions of past year kratom users. The PDP for LSD use recency as well as cocaine recency and its effect on past year kratom use were similar. If respondents used LSD or cocaine more than 12 months ago, or never used the drug at all, it had more effect on predictions of past year kratom users. The only difference was that those who never used LSD or cocaine slightly predicted more. Additionally, the PDP for those who used stimulants not directed by their doctor to get high and past year kratom use showed differing effects on model predictions. Those who had never used/misused stimulants were related to the outcome variable, past year kratom use, the most meaning these variables had more effect on the model's predictions. Lastly, the PDP of past year kratom use based on age shows the probability is low until about 20 years old and increases after, peaking at around the late 20s to early 30s range.

Model 2 (2020) had an OOB error rate of 0.88%. The random forest model wrongly classified the OOB sample 0.88% of the time, which is highly accurate. A confusion matrix was also computed for Model 2 to further interpret the results as seen in Figure 3.

Model 2 Confusion Matrix

	No Kratom Use in Past Year	Kratom Use in Past Year	Class Error
No Kratom Use in Past Year	13661	0	0
Kratom Use in Past Year	120	0	1

Figure 3. Random Forest Results for Model 2

Model 2 accuracy suggested that it was not able to predict past-year kratom users. However, like Model 1, it was extremely accurate in predicting individuals who did not use kratom in the past year. When reviewing the Gini and MDA scores for past-year kratom users, the high-importance variables overlapped slightly once more. The top high-importance variables for the MDA were the respondent's level of impairment due to mental health, age, perceived mental health issue, perceived difficulty in obtaining LSD, and perceived difficulty in obtaining heroin. The high-importance predictors for the Gini index were the respondent's level of impairment score, the legal penalty in their state for marijuana possession, the number of times they had visited the doctor in the past year, age, and perceived difficulty in obtaining LSD.

Figure 4. Top Predictors for Each Year (Mean Decrease Accuracy)

	Top Predictors for Each Year - Mean Decrease Accuracy	
2019	2020	2021
Perceived Difficulty to Obtain Marijuana	Level of Impairment	Age
LSD-use Recency	Age	Frequency of Religious Services
Stimulant Use to Get High	Perceived Mental Health Issue	Stimulant-use Recency
Age	Perceived Difficulty to Obtain LSD	Feelings About Adult Drug Use
Cocaine-use Recency	Perceived Difficulty to Obtain Heroin	Past-year Alcohol Disorder

Figure 5. Top Predictors for Each Year (Gini Index)

	Top Predictors for Each Year - Gini Index	
2019	2020	2021
Level of Impairment	Level of Impairment	Level of Impairment
Num. Times Visited Doctor in PY	Legal Penalty for Marijuana	Perceived Difficulty to Obtain Crack
Age	Num. Times Visited Doctor in PY	Perceived Difficulty to Obtain Heroin
Legal Penalty for Marijuana	Age	Perceived Difficulty to Obtain Cocaine
Perceived Difficulty to Obtain LSD	Perceived Difficulty to Obtain LSD	Legal Penalty for Marijuana

PDPs were also computed on the top five important predictors for the MDA. The PDP for past-year kratom use and the level of impairment score given to the respondent[7] shows that the probability for kratom use is highest between scores of 1-3 and then lowers as the score increases. In contrast, the PDP for past-year kratom use and the respondent's age shows that the probability for kratom use is low until age 19 and peaks at late 20s and early 30s, meaning the most predictions were made at these ages. The PDP for past-year kratom use and the respondent's perceived mental health issues showed similar effects on the model, with those who did not think they had a mental health issue with slightly more predictions. Lastly, the PDPs for past-year kratom use and heroin recency as well as LSD recency similarly affected the model. The most predictions of kratom use came from those who found that LSD and heroin were "Very Difficult" to obtain, with the fewest predictions coming from those who found it "Fairly Easy" to obtain LSD and "Very Easy" to obtain heroin.

Lastly, for Model 3 (2021), the OOB error rate was 0.82%. The random forest wrongly classified the OOB sample 0.82% of the time, which is similarly accurate to Model 2. A confusion matrix was computed to further investigate the result as seen in Figure 4.

Model 3 Confusion Matrix

	No Kratom Use in Past Year	Kratom Use in Past Year	Class Error
No Kratom Use in Past Year	24573	0	0
Kratom Use in Past Year	204	0	1

Figure 6. Random Forest Results for Model 3

Model 3 accuracy suggested that it was, again, not able to predict past-year kratom users. However, like Models 1 and 2, it was extremely accurate in predicting individuals who did not use kratom

[7] This is based on gauged impairment on daily activities due to the respondent's mental health.

in the past year. When reviewing the Gini and MDA scores for past-year kratom users, the high-importance variables did not overlap. The top high-importance variables for the MDA were the respondent's age, how often they attended religious services, stimulant-use recency, how they felt about adult drug use, and past-year alcohol disorder. The high-importance predictors for the Gini index were the respondent's level of impairment score, perceived difficulty in obtaining crack, perceived difficulty in obtaining heroin, perceived difficulty in obtaining cocaine, and the legal penalty in their state for marijuana possession. Further, PDPs were computed for each of the top five important predictors. The PDP for past-year kratom use and the respondent's age showed the probability for kratom use was low until age 18-20, with the highest probability being in the mid 30s to late 40s. The following PDP for past-year kratom use and the number of times respondents had attended a religious service in the past year showed decently similar effects on predictions, with attending no religious services predicting the majority of kratom use. Additionally, the PDP for past-year kratom use and stimulant-use recency showed most predictions of kratom use were made by those who indicated they had never used stimulants. The PDP for past-year kratom use and how the respondent felt about adult drug use showed very similar effects on predictions, with indifference showing slightly more predictions for kratom use. Finally, the PDP for past-year kratom use and whether the respondent had an alcohol disorder in the past year also showed similar effects on predictions, with those not having a disorder slightly predicting more.

4.2. Research Question 2: predicting kratom use when isolating opioid users

In Model 4, a random forest was implemented to identify if it was possible to predict past year kratom users out of the NSDUH datasets by the same characteristics. However, differing from Models 1-3, opioid users were isolated and pulled from the 2019-2021 datasets by those who misused opioids in the past year and combined into one dataset. Opioid misuse was now held constant to see if the important variables identified in predicting kratom use differed from those in Models 1-3. The random forest model was trained using the split training sample to predict the past-year kratom users. In Model 4, the random forest wrongly classified the OOB sample 3.83% of the time. A confusion matrix was computed to further review the finding which can be seen in Figure 5.

Model 4 Confusion Matrix

	No Kratom Use in Past Year	Kratom Use in Past Year	Class Error
No Kratom Use in Past Year	1880	0	0
Kratom Use in Past Year	76	0	1

Figure 7. Random Forest Results for Model 4

Model 4 accuracy suggested that it was not able to predict past-year kratom users. However, like Models 1-3, it was extremely accurate in predicting individuals who did not use kratom in the past year. When reviewing the Gini and MDA scores for past year kratom users, the high-importance variables did not overlap. However, some of the variables were related. For example, pain reliever recency was included for the MDA, where the main reason people misused pain relievers was included in the Gini. The top predictors for the MDA included past-year meth disorder, past-year heroin disorder, pain reliever-use recency, if respondents had ever been active-duty military, and if they took stimulants not directed by a doctor to get high. For the Gini index, the top predictors were the respondent's past-year serious psychological distress indicator, the main reason they had misused pain relievers, the legal penalty in their state for marijuana possession, and if they used stimulants not directed by a doctor to get high. PDPs were computed for the Model 4 top predictors of past-year kratom use. The PDP for past-year kratom use and if the respondent had a meth disorder in the past year showed those who never used meth had the most predictions in kratom use. The fewest predictions were made for those who had not used meth in the past year. Similarly, the PDP for past-year kratom use and having a heroin-use disorder in the past year showed those who didn't have a disorder in the past year predicted the majority of kratom use. Additionally, the fewest predictions were made from those who exhibited a heroin-use disorder in the past year. A PDP was done for past-year kratom use and the respondents' pain reliever-use recency with the highest number of predictions coming from those who had used pain relievers in the past year. The fewest predictions were from those who had used pain relievers more than a year ago. Past-year kratom use and if the respondent had ever been on active duty showed similar effects on predictions, with serving and not serving having equal predictions. Lastly, the final PDP was regarding past-year kratom use and the respondent's use of stimulants that were not directed by a doctor to get high. The highest number of predictions came from those who had never used or misused stimulants, with those who indicated they had not used stimulants specifically to get high with the fewest predictions.

4.3. Research Question 3: predicting opioid cessation with kratom use now a predictor

In Model 5, a random forest was implemented to identify if it was possible to predict opioid cessation of opioid users within the NSDUH datasets using the same variables. However, differing from Models 1-4, opioid users were isolated by separating pain reliever users and pulling them from the 2019-2021 datasets to combine into one dataset. Additionally, past-year kratom use became a predictor, making the outcome variable a pain reliever-misuse recency variable. With this outcome variable, we were able to see those who had used prior but had stopped using within the past year. Like Model 4, pain reliever use was now held constant to see if kratom use was identified as being an important predictor of opioid cessation. This random forest model was trained using the split training sample to predict opioid cessation. Lastly, in Model 5, the random forest wrongly classified the OOB sample at an error rate of 13.77%. This means the model's predictions were wrong 13.77% of the time. A confusion matrix was computed to further review the finding which can be seen in Figure 6.

Model 5 Confusion Matrix			
	Misused Opioids in Past Year	No Opioid Misuse in Past Year	Class Error
Misused Opioids in Past Year	1824	47	.025
No Opioid Misuse in Past Year	376	825	.313

Figure 8. Random Forest Results for Model 5

Overall, the accuracy of the random forest model was high for the outcome variable. Like the models before, it was extremely accurate in predicting those who had misused pain relievers in the past year. However, differing from the prior models, the model was able to predict those who experienced opioid cessation, defined as those who had used more than 12 months ago. Specifically, the random forest incorrectly predicted opioid cessation 31.3% of the time, which is acceptable. When reviewing the Gini and MDA scores for those who had abstained from misusing pain relievers, the high importance variables overlapped greatly. The top predictors for the MDA scores were the use of pain relievers not directed by a doctor for pain relief, pain reliever use without a prescription in the past year, the survey year, the use of pain relievers in another fashion in the past year and oxycontin use not directed by a doctor. The top predictors for the Gini index included pain reliever use without a prescription in the past year, the use of pain reliever use not directed by a doctor for pain relief , pain reliever use not directed by a doctor to get high, pain reliever misuse disorder in the past year, and taking pain relievers more than their prescription stated in the past year.

Following the importance computation, PDPs were constructed for the top predictors of whether a respondent abstained from pain reliever misuse. The PDP for opioid cessation and the usage of illicit pain reliever use for pain relief showed that those who used had the largest effect on predicting whether someone abstained from opioid misuse. Those who did not use in the past year had the lowest effect on predictions. The PDP created for opioid cessation and usage of pain relievers without a prescription in the past year showed those who used pain relievers without a prescription had the most effect on opioid cessation predictions, with those who had not used in the past year influencing the fewest predictions. Similarly, the PDP for opioid cessation and oxycontin use not directed by a doctor showed that respondents who used oxycontin were responsible for the highest number of predictions for whether individuals were able to abstain from opioid misuse. The fewest predictions for opioid cessation were attributed to those who had not used oxycontin. Interestingly, the PDP of opioid cessation and the year variable showed that individuals from the 2021 NSDUH influenced the most predictions of opioid misuse cessation. Predictions were low for 2020 and 2019. The final PDP computed for opioid cessation and past-year pain reliever use in another way not listed in the NSDUH showed that those who used pain relievers had the most effect on whether someone misused opioids. Those who did not use in the past year had the lowest effect on predictions.

CHAPTER 5: DISCUSSION AND CONCLUSION

5.1. Significance and Limitations

Significance

There are a few significant points resulting from this study. This study is currently alone in its attempt to identify the predictors of kratom use using machine-learning techniques. Importantly, this represents the most recent dataset available in the United States that was formally collected. As a result, the machine-learning analyses performed in this study have implications for policy and further research.

Regarding the research questions posed, the random forest model was not able to predict kratom use in Models 1-4, which was significant in answering Research Question 1. However, it was extremely accurate when predicting kratom non-users. This prompts us to confirm that kratom use and what leads individuals to use kratom is still unknown and requires further inspection. A respectable amount of literature exists on the potential link between opioid use and kratom use, which was used to guide Research Question 2. Despite the various literature suggesting a link between opioid use and kratom use, when opioid users were isolated in Model 4, the important predictors differed from those in the general analysis. This suggests that predictors of kratom use may differ for opioid users as opposed to kratom users who may not have used opioids. This is also important in that the motivations for kratom use noted in existing research heavily focus on prior or current opioid use or misuse, when perhaps there are other important use motivations currently undiscovered. Further, the results of this study throw uncertainty on the link between opioid use and kratom use and thus should be further examined. Two variables that consistently returned as high-importance predictors are also worth mentioning. The level of impairment score consistently presented as the highest predictor in Models 1-3. The impact of one's mental health on daily activities, such as attending social outings, may influence whether someone uses kratom. Additionally, the variable concerning the legal penalty for possession of marijuana in the respondent's state was present in the top five important predictors for four of the five models, which is significant. Potential legal sanctions may be considered when individuals choose to use kratom.

Lastly, research has also posited that kratom use may have therapeutic value when it comes to helping opioid misusers cease use and perhaps abstain from opioids altogether. However, when looking at individuals who reported kratom use in the past year, it was found to not be an important predictor of people who had reported prior opioid misuse more than 12 months ago but no longer used within the past year (Model 5). While this analysis's results did not show kratom use as an important predictor, it shows that further research is needed to determine kratom's role in opioid cessation.

Limitations

As with all research, this study has limitations that require some discussion. First, it is recognized that the NSDUH is the primary nationally-representative dataset of drug use and mental illness estimates of civilian, noninstitutionalized people in the United States (CDC, 2022). Additionally, the NSDUH is designed to be highly confidential (NSDUH, 2021). Despite its private administration, the data relies on self-reported drug use. The value of the responses rely on the respondent's memory and their willingness to be forthcoming. Additionally, this survey is cross-sectional, meaning that the respondents were interviewed once without follow-up. Therefore, the NSDUH does not capture drug use and mental illness over time, which can be extremely beneficial for research. Likewise, since the survey captures responses from civilian, noninstitutionalized individuals in the United States, part of the population is excluded. As noted by the NSDUH (2021), people in the excluded subgroups—such as current active-duty military members or incarcerated individuals—were not recorded. It's possible that the drug use and mental illness patterns in these subgroups may differ and therefore provide inaccurate prevalence estimates of the total population. This especially could be the case for less commonly-used drugs, such as kratom.

One of the major limitations of this study is the lack of uniformity across the 2019, 2020, and 2021 NSDUH used in the analyses. There are several parts to this limitation, with each part being addressed regarding data collection methods, nonresponse bias, and differential use of the Diagnostic and Statistical Manual of Mental Disorders (DSM) to guide the substance-use disorder sections in each survey. Starting with data collection, each survey included in this study differed in its methodology, specifically the data collection methods. The 2019 survey followed the normal procedure of screening individuals in a household and then following up with an in-person interview to collect data. However, due to the COVID-19 pandemic in 2020, the 2020 NSDUH was significantly impacted.[8] Data collection was typically facilitated through in-person interactions, which was halted during the 2020 collection period. By the end of the collection period, the collection method had evolved to online interviews and very few in-person interviews in comparison to the previous year. Further, due to the pandemic, fewer responses were seen across the survey which thus impacted potential response bias. In addition to response bias, the 2020 NSDUH suffered from more missingness than the 2019 or 2021 surveys. This can be attributed to COVID-19. Lastly, for the 2021 NSDUH, data collection remained mixed with online and in-

[8] Please see Appendix for more details concerning the impact of COVID-19 on the 2020 NSDUH.

person interviews throughout the entire year due to safety precautions. Overall, the pandemic disrupted the cohesiveness of data collection methods following 2019.

Likewise, it is important to note that missingness across all three datasets was common. This limited the use of several potential predictors for this analysis. It is possible to consider that one of the variables omitted from the analysis due to missingness could be an important predictor of kratom use. Another potential effect of nonresponse bias and missingness in the datasets could contribute to low number of kratom users in the primary sample. Out of 117,200 observations (N=117,200), there were less than 700 adult kratom users. This led to an imbalance in the datasets which ultimately led to higher accuracy in predicting those who did not use kratom. Additionally, another limitation of this study can be identified by the NSDUH's use of different DSM versions in each survey. The DSM was used to guide questions and subsequent variables created from these questions in sections focused on mental illness and substance use disorders. This is important to note as the 2019 survey used the DSM-IV version 2020 used the DSM-IV and DSM-V, and 2021 used only the DSM-V. Due to the use of multiple versions of the DSM for guiding survey questions, wording differed across the three surveys. This was especially seen in the substance use disorder sections. It must be acknowledged that respondents may have interpreted the questions differently and thus influenced the way they responded. This may have created inconsistent response data across the 2019-2021 surveys which may have influenced the predictors used in this analysis.

5.2. Policy Implications and Future Research

Looking ahead, these findings have important implications. Regarding future research, there are a few ways the limitations could be mitigated if this study were to be replicated. For example, future research may conduct this analysis after a few years have passed to help mitigate the pandemic-related disruptions, such as nonresponse bias and missingness. Additionally, it may be important for research to replicate the analyses in the future when there are more datasets available using the DSM-V to mitigate the variation between the substance abuse and disorder questions. Further, by using datasets that followed the same DSM guidelines, it will be less likely that participants would interpret the questions differently. For this study, 2019 is the first time kratom use is posed to participants. As it continues to be included in the NSDUH, there will be more datasets for research to choose from when curating their analytic plan to avoid COVID-19 disruptions as well as varying uses of the DSM. Lastly, regarding the isolation of opioid users to see if kratom use could be predicted, it was found that the important predictors differed than that of the general sample. Future research should consider the possibility that the predictors of kratom users may be different than opioid users who also use kratom. The motivations could be separate and thus should be further explored.

Regarding policy, kratom is currently legal in the United States at the federal level and has yet to be scheduled by the DEA or banned by the FDA. With the use of a highly sophisticated machine learning model, attempts at predicting kratom use were unsuccessful. The recurring top important predictors of whether someone used kratom, level of impairment and the legal penalty for possession of marijuana, are important to consider when informing policy. Policymakers should consider mental health treatment alternatives, such as kratom, as a potential option for mitigating mental health symptoms. Likewise, it appears that kratom use is influenced by the respondent's consideration of legal sanctions associated with being caught with possession of marijuana in their state. Kratom's legality in the United States may influence those who participate in drug use to switch to less consequential options. This is important for policy to consider as states with lenient marijuana possession sanctions may not be effectively deterring drug users from illicit drug use.

This study was also unsuccessful in highlighting kratom use as an important predictor for those who had abstained from opioid misuse. This doesn't mean kratom can be completely ruled out as beneficial in the opioid cessation process. However, it does mean that opioid misusers in the United States are finding other ways to successfully cease opioid use. Policy should continue to support opioid misuse treatment and provide more accessible and affordable ways for individuals to seek medicinal help. While kratom may be useful in assisting withdrawal symptoms or help lessen opioid use, the results throw doubt on its ability to help opioid misusers completely abstain from opioid misuse. Therefore, policymakers should continue to explore additional ways in improving treatment options for those experiencing opioid misuse.

Overall, while the results create more questions, it does highlight the need for further research. U.S. kratom users are extremely understudied due to its recent emergence in drug culture. The lack of prevalence data and formal datasets on U.S. kratom users should be addressed and continuously included in attempts to gauge drug use. This will help capture a better picture of kratom use. This study also provides insight into other potential avenues in predicting kratom use. Two predictors, legal penalties regarding possession of marijuana and one's level of impairment due to their mental health, consistently showed up in the main important predictors of whether respondents used kratom. The literature heavily focuses on the link between opioid use/misuse and kratom use, but this study highlights potential links to be explored that have not been assessed previously.

Additionally, this study attempted to confirm if kratom was a strong predictor of opioid cessation, since kratom use has been consistently seen to be used to wean off opioids or mitigate withdrawal symptoms. While kratom use was not a strong predictor in this analysis, kratom use as a way of harm reduction or managing withdrawal symptoms from opioids in previous literature is hard to dismiss. More attempts are required to investigate the link between opioid use and kratom use. Further, future research should continue to focus on what predicts kratom use to identify if the drug truly has therapeutic benefits or should be avoided in medicinal situations.

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APPENDIX: ADDITIONAL INFORMATION

Figure 1

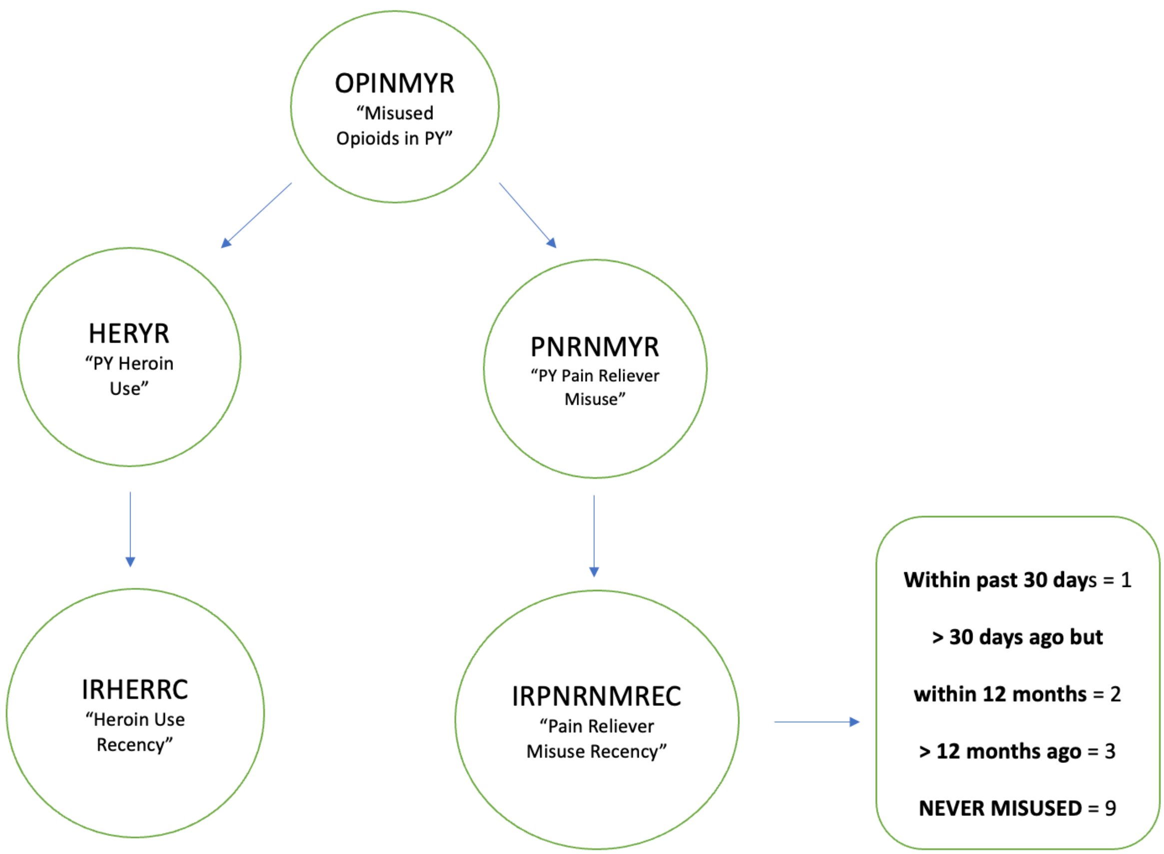

Figure 1. Outcome Variable Breakdown for Opioid Cessation Outcome Variable

Table 2. List of Variables

Code	*Description*
KRATOMYR	Past year kratom use
OPINMYR	Past year opioid misuse
OXCNNMYR	Past year oxycontin misuse
PNRNMINIT	Past year initiate for pain reliever misuse

PNRWYNORX	Past year pain reliever use without an RX
PNRWYGAMT	Used pain reliever in greater amounts than RX in past year
PNRWYOFTN	Used pain reliever more often than RX in past year
PNRWYLNGR	Used pain reliever longer than RX in past year
PNRWYOTWY	Used pain reliever in another way not directed in past year
PNRRSPAIN	Used pain reliever (not prescribed) to relieve pain
PNRRSRELX	Used pain reliever (not prescribed) to relax
PNRRSEXPT	Used pain reliever (not prescribed) to experiment
PNRRSHIGH	Used pain reliever (not prescribed) to get high
PNRRSSLEP	Used pain reliever (not prescribed) to sleep
PNRRSEMOT	Used pain reliever (not prescribed) for emotions
TRQNMINIT	Past year initiate for pain tranquilizer misuse
TRQRSRELX	Used tranquilizer (not prescribed) to relax
TRQRSEXPT	Used tranquilizer (not prescribed) to experiment
TRQRSHIGH	Used tranquilizer (not prescribed) to get high
TRQRSSLEP	Used tranquilizer (not prescribed) to sleep
STMNMINIT	Past year initiate for stimulant misuse
STMWYNORX	Used stimulant without RX in past 12 months
STMWYGAMT	Used stimulant in greater amounts than RX in past year
STMRSWGHT	Used stimulant (not prescribed) to lose weight
STMRSCONC	Used stimulant (not prescribed) to concentrate
STMRSALRT	Used stimulant (not prescribed) to stay alert
STMRSSTDY	Used stimulant (not prescribed) to study
STMRSEXPT	Used stimulant (not prescribed) to experiment
STMRSHIGH	Used stimulant (not prescribed) to get high
SEDNMINIT	Past year initiate for sedative misuse

SEDWYNORX	Used sedative without RX in past 12 months
SEDWYGAMT	Used sedative in greater amounts than RX in past year
SEDWYOFTN	Used sedative more often than RX in past year
SEDWYLNGR	Used sedative longer than RX in past year
SEDRSRELX	Used sedative (not prescribed) to relax
SEDRSEXPT	Used sedative (not prescribed) to experiment
SEDRSHIGH	Used sedative (not prescribed) to get high
SEDRSSLEP	Used sedative (not prescribed) to sleep
SEDRSEMOT	Used sedative (not prescribed) for emotions
IRALCRC	Alcohol recency
IRMJRC	Marijuana recency
IRCOCRC	Cocaine recency
IRCRKRC	Crack Cocaine recency
IRHERRC	Heroin recency
IRHALLUCREC	Hallucinogens recency
IRLSDRC	LSD recency
IRECSTMOREC	Ecstasy or Molly recency
IRKETMINREC	Ketamine recency
IRDAMTFXREC	DAMT/FOXY recency
IRINHALREC	Inhalants recency
IRMETHAMREC	Meth recency
IRPNRANYREC	Any pain reliever recency
IROXCNANYYR	Any oxycontin recency
IRTRQANYREC	Any tranquilizer recency
IRSTMANYREC	Any stimulant recency
IRSEDANYREC	Any sedative recency
IRPNRNMREC	Pain reliever misuse recency
IROXCNNMYR	Past year oxycontin misuse

IRTRQNMREC	Tranquilizer misuse recency
IRSTMNMREC	Stimulant misuse recency
IRSEDNMREC	Sedative misuse recency
PNRMAINRSN	Main reason for misusing pain relievers
TRQMAINRSN	Main reason for misusing tranquilizers
STMMAINRSN	Main reason for misusing stimulants
SEDMAINRSN	Main reason for misusing sedatives
RSKHERTRY	Risk of using heroin
RSKHERWK	Risk of using heroin a couple times in a week
RSKCOCMON	Risk of using cocaine one a month
RSKCOCWK	Risk of using cocaine a couple times a week
DIFGETMRJ	Perceived difficulty of getting marijuana
DIFGETLSD	Perceived difficulty of getting LSD
DIFGETCOC	Perceived difficulty of getting cocaine
DIFGETCRK	Perceived difficulty of getting crack cocaine
DIFGETHER	Perceived difficulty of getting heroin
PYUD5ALC	Past year alcohol use disorder
PYUD5MRJ	Past year marijuana use disorder
PYUD5COC	Past year cocaine use disorder
PYUD5HAL	Past year hallucinogen use disorder
PYUD5INH	Past year inhalant use disorder
PYUD5MTH	Past year meth use disorder
PYUD5HER	Past year heroin use disorder
EDUD5PNRMIS	Pain reliever use disorder past year misusers
UD5OPIANY	Opioid use disorder past year misusers
UD5HRPNRMIS	Heroin and pain reliver use disorder past year misusers
BOOKED	Ever been arrested and booked
NOBOOKY2	Number of times arrested and booked

MXMJPNLT	Penalty for marijuana possession in your state
PAROL	Parole status
PROB	Probation status
TXSHGWENT	Went to self-help group in past year
TXEVRRCVD2	Received treatment at any location for illegal drug use or alcohol use
TXYRILL	Received treatment at any location for illegal drug use in past year
TXYRRECVD2	Received treatment at any location for illegal drug use or alcohol use in past year
TXYRUSEHER2	Received treatment for heroin use in past year
TXYRUSEPNR2	Received treatment for pain reliever use in past year
TXLTPYHINS2	Last/current treatment for illegal drug/alcohol use was covered by insurance
TXLTPYMCRE2	Last/current treatment for illegal drug/alcohol use was covered by Medicare
TXLTPYMCAD2	Last/current treatment for illegal drug/alcohol use was covered by Medicaid
TXLTPYPUBL2	Last/current treatment for illegal drug/alcohol use was covered by public assistance
INHOSPYR	Stayed overnight in hospital in past year
NMVSOPT2	Number of times seen doctor in past year
NMVSOEST	Number of times seen doctor about health in past year
HRTCONDEV	Diagnosed with heart condition
DIABETEVR	Diagnosed with diabetes
COPDEVER	Diagnosed with COPD
CIRROSEVR	Diagnosed with cirrhosis
HEPBCEVER	Diagnosed with Hep B or C
KIDNYDSEV	Diagnosed with kidney disease
ASTHMAEVR	Diagnosed with asthma
CANCEREVR	Diagnosed with cancer
HIGHBPEVR	Diagnosed with high blood pressure
CANCERYR	Diagnosed with cancer in the past year

PREG	Pregnant
AUALTYR	Received alternative treatment for mental health in past year
AMHINP2	Received inpatient treatment for mental health in past year
AMHOUTP4	Received outpatient care for mental health in past year
AMHRX2	Received prescription medication for mental health in past year
AMHTXND2	Perceived unmet needs/treatment for mental health in past year
SNYSELL	History of selling illegal drugs
SNFAMJEV	Perception of adult marijuana use
SNRLGSVC	Frequency of attending religious services
SNRLGIMP	How important your beliefs are to you
SNRLDCSN	Religious beliefs influence your decisions
SPDPSTYR	Serious psychological distress in the past year
WHODASTOTSC	Level of impairment score
IRAMDELT	Adult lifetime major depressive episode
IRAMDEYR	Past year adult major depressive episode
CASUPROB2	Perceived ever had alcohol or drug use problem
RCVYSUBPRB	Perceived recovery from suspected alcohol or drug problem
CAMHPROB2	Perceived ever had mental health problem
RCVYMHPRB	Perceived recovery from suspected mental health problem
OPMATYR2	Received opioid medication-assisted treatment in past year
AGE3	Age of respondent
SERVICE	Military service lifetime
ACTDEVER	Active-duty lifetime
SEXIDENT	Sexual identification
IRSEX	Gender
IRMARIT	Marital status

NEWRACE2	Race
EDUHIGHCAT	Education
HEALTH2	Overall health
WRKDPSTYR	Past year work situation
WRKSELFEM	Self-employed in past year
WRKNJBPYR	Unemployed in past year
WRKDRGPOL	Workplace drug policy
WRKDRGHLP	Workplace drug or alcohol assistance
WRKTSTDRG	Workplace drug testing
WRKTSTHIR	Hiring process includes drug testing
IRWRKSTAT18	Recode - employment categories
IRINSUR4	Overall health insurance coverage of respondents
OTHINS	Overall other health insurance coverage of respondents
INCOME	Income

3. Impact of COVID-19 on the 2020 NSDUH Survey

The NSDUH collects data in quarter increments throughout the year. Historically, data collection methods have been through in-person interviews within people's homes. However, in March of 2020, this changed dramatically. Due to the pandemic, all data collection stopped at the end of the first quarter. Collection continued to be suspended due to extreme safety concerns of interviewers and interviewees. However, in July of 2020, SAMHSA approved a small-scale attempt to collect in-person data once more – completely guided by the current safety protocols. Web-based interviews were eventually approved, and data collection once more picked up in 4th quarter. Despite data collection resuming, there were essentially no data collected in Quarter 2 or 3.

The target sample for the 2020 NSDUH was 67,500 people across the U.S. The final sample included 36,284 people, which was significantly off target. Concerning the weighted response rates, the rates for household screening and for interviewing were 25.7 and 60.4 percent. The overall response rate was 15.5 percent for people aged 12 or older. The weighted interview response rates was 62.8 percent for adults. While the sample for 2020 was lower than the target number of people, the NSDUH found that only a few estimates in the report was suppressed due to its low statistical precision (NSDUH, 2020).

Overall, the NSDUH experienced extreme methodological changes. Web-based interviews were introduced into the 2020 NSDUH, which had never been done before. Additionally, there was a significant gap in data collection. The NSDUH highlights that some research has found that the pandemic had serious effects on drug use and mental health, which could have impacted the results.