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Representative national survey on drug use during the COVID-19 stay-at-home order in the USA

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ABSTRACT

Objectives This study explores the drug use behaviour in the US general population in the early days of the COVID-19 pandemic with a focus on the relationship between sociopsychological factors, mobility restrictions from March to June 2020 and mental health conditions.

Design A retrospective anonymous online survey representing a cross-section of the US population in 2020.

Setting A qualified panel of 500 000 Qualtrics participants stratified by gender, race, age and geographical region to represent the US population.

Participants 3340 participants voluntarily consented to respond.

Measures Outcome measure for illicit and non-medical use of prescription drugs based on the National Institute on Drug Abuse-Modified Alcohol, Smoking and Substance Involvement Screening Test Level-2 Substance Use for Adult Questionnaire and predictor measures include self-reports of mobility behaviours, demographics and mental states using psychometrically validated scales.

Results χ^2 tests showed that those who stayed home reported higher odds ($p<0.05$) of use across all 10 types of drugs. Logistic regression revealed that those with children at home, larger social circles, and pain, depression or trauma had higher odds, but older individuals and women had lower odds ($p<0.05$) of drug use.

Conclusions Mobility restriction was a risk factor for drug use. Demographics and mental health conditions were important covariates, underscoring the need for further research on unintended consequences of infection control policies during national health crises.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ Statistically representative sample of the general population in the USA.
⇒ The study focuses on drug use and mobility restriction during the COVID-19 pandemic, whereas most studies on this topic focused on alcohol or tobacco consumption and did not directly measure but assumed mobility restriction.
⇒ Employs validated and well-accepted measures for drug use, mental states and social networks.
⇒ Data consist of self-reports, which may have response bias.
⇒ Cross-sectional data limit the determination of causality.

BACKGROUND

COVID-19 (SARS-CoV-2), a fast-spreading viral respiratory illness, arrived in the USA in January 2020.[1] In March 2020, the US Federal government responded with a 'stay-at-home' or mobility restriction policy to contain its spread to prevent healthcare facilities from being overwhelmed by rapidly mounting cases.[2 3] The infection control measures included stay-at-home orders, closure of schools, non-essential businesses, parks and entertainment facilities, as well as physical distancing in public places. The stay-at-home order altered familiar daily routines and mobility behaviours.[4] For example, the closure of schools forced parents to stay at home and homeschool their children, which increased mental stress.[5] The curtailment of social activities in public places and entertainment facilities significantly reduced in-person interactions, which increased social isolation, boredom and depression.[5 6] The daily broadcast, social and print media reporting on the pandemic created stress.[7 8] Stress is a known risk factor for a range of mental disorders.[9] Hence, there are reports of poor mental disorders, such as depression, anxiety and pain, during this period.[10 11] Mental disorders are associated with drug misuse.[12–14] The pandemic's lockdowns and social distancing measures have exacerbated drug use by heightening isolation, stress and economic insecurity.[15] Some individuals started or increased drug use as a maladaptive coping mechanism for stress related to COVID-19.[16 17 18] Maladaptive coping occurs when individuals deal with stressors that create fear, anxiety and/or worry by overconsuming food, tobacco, alcohol and drugs to avoid displeasure, boredom and monotony.[19–22]

There are many studies on maladaptive coping related to food, tobacco and alcohol consumption during the COVID-19 pandemic, but less research on various types of drug use and mobility restriction.[23] The mobility restrictions (ie, stay-at-home orders) of COVID-19 may be associated with maladaptive coping behaviour risks. In this regard, we focus on drug use in the general population since it is relatively less well studied. According to an analysis by the US White House Office of National Drug Control Policy, the economic cost of substance use disorders was estimated at US$193 billion in 2007 due to lost productivity, costs of treatment and criminal justice costs.[24] Hence, understanding the link between COVID-19 and drug use can add to a better estimate of the economic effects of the pandemic, besides its public health and clinical effects. In this study, we seek to understand drug use in the US general population and its socioeconomic and mental health correlates during the early stages of the COVID-19 pandemic. We do this with a representative population survey, developed from the theory of motivated behaviours. We focus on the period just after the movement restrictions or 'lockdowns' were imposed in March 2020. To our knowledge, this is the only survey of drug use in the general population in close proximity to the early days of the pandemic.

There has been some research on the biological and behavioural factors related to drug use during COVID-19. For example, individuals who regularly use drugs are at increased risk for infection, experience higher rates of severe illness and face unique sociopsychological challenges stemming from compromised immune systems, co-occurring medical conditions, poor health-seeking behaviours and barriers to accessing treatment.[25] Biologically, opioids, methamphetamine, cocaine and other illicit drugs disrupt normal immune function and overall respiratory health, making individuals more susceptible to respiratory infections.[26] For instance, opioid use depresses respiratory function.[26] Chronic methamphetamine use can compromise cardiopulmonary function.[27] When coupled with COVID-19, these pre-existing vulnerabilities dramatically escalate morbidity and mortality.

Behaviourally, individuals recovering from drug use rely on in-person support networks such as group counselling, 12-step meetings or community harm-reduction services. COVID-19-related mobility disruptions left a void in essential support systems. Telemedicine and virtual group sessions attempted to fill the gap, but not all individuals had consistent access to reliable internet or digital devices, hindering widespread adoption.[28] As well, the stigma surrounding addiction may have deterred individuals from seeking emergency care or COVID-19 testing due to fear of legal consequences or judgement.[15]

During the pandemic, studies consistently reported a rise in overdose deaths, particularly opioid-related fatalities.[25] This may be attributed to disrupted drug markets, increased adulteration of substances and users being forced to consume drugs in isolation so that timely medical intervention was less likely in the event of overdose.[28] Harm reduction services, such as needle exchange programmes and supervised consumption sites, also faced pandemic-related constraints, reducing their capacity to effectively serve marginalised populations.

Studies on specific drugs, such as methamphetamine, used during the COVID-19 pandemic come from Europe,[29–33] which report increases, while studies in the US focused largely on cannabis and opioids.[12 32] Yet, the National Institute on Drug Abuse (NIDA) is focused on 10 types of illicit and prescription drugs (opioids, prescription stimulants, sedatives, cocaine, club drugs, hallucinogens, heroin, inhalants, cannabis and methamphetamine) consumed for non-medical purposes.[34] Moreover, the studies on drug use during COVID-19 in the USA reported mixed findings[32 35 36] and focused on youths and high school adolescents.[37–39] While there was an overall increase in the use of cannabis,[40] the trend for drug use by young adults decreased,[38 39 41 42] but there was no consistent change for older persons.[43] The decline in substance use among youths during the stay-at-home order may reflect in part on fewer opportunities for social interactions associated with recreational drug consumption among friends.[36 39 41 42 44] Research reports also indicate that men were more likely than women to use all types of illicit drugs.[45] Researchers have noted that household disruptions, such as increased burdens in childcare and homeschooling responsibilities, due to the forced closure of childcare facilities, public schools and playgrounds, caused significant psychological distress among adults with children at home, which may result in a heightened risk of prescription drug overuse.[4]

Understanding the relationship between reduced mobility (or staying home) and factors associated with 10 types of drug use for non-medical reasons in the general US population will fill a gap in the extant literature. We hypothesise that individuals whose mobility was restricted and daily life activities impacted by the stay-at-home order would report negative mental states and a positive association with drug use. We test our hypothesis with a comprehensive survey of substance use to include respondents' self-reports of the 10 drugs used listed in NIDA's Quick Screen tool,[34] mobility behaviours, demographics, social networks and mental states during the stay-at-home order in the USA. By understanding who may be vulnerable to increased drug use during periods of community isolation would help policy-makers mitigate those risks with adjuvant interventions in future events.

METHODS

Setting, data collection and sample

Data were collected through a cross-sectional survey of 500 000 Qualtrics XM panel unique participants stratified by gender, race, age and geographical region to represent the US population (see online supplemental survey instrument). The inclusion criteria consisted of participants over 18 years of age who consented to participate anonymously in the survey. Participants were assigned

a unique number based on their media access control address that is not connected to their personal information, at the time of the survey, to ensure they participated only once. Participants were paid a US$5.15 incentive to participate in a survey that took an average of 13 min to complete. The incentive was paid to improve response rates and standardise the respondent motivations to minimise bias. The survey had to be completed in one sitting. Data quality was checked at the point of collection. These included manipulation checks for respondent fatigue, respondent inattention, social desirability and order of question effects. The survey was conducted over 3 days in June 2020 with 3340 individuals from all 50 States plus the District of Columbia responding. Based on the sample size calculation, we determined that 3000 responses were sufficient to achieve statistical power at $p<0.05$ significance. An additional 340 responses were received within a day of the survey closing, bringing the total sample to 3340. The response data were checked against the general population characteristics, based on the latest US Census Data, to ensure representativeness (ie, no statistical differences) in distribution according to gender, race, age and geographical region. Only fully completed surveys were included in the final dataset, and so there were no missing values. Data security on the Qualtrics platform is assured by the latest ISO and FedRAMP (standard of US government security compliance, with over 300 controls based on NIST 800-53 that requires periodic independent assessments) technology (https://www.qualtrics.com/security-statement/, accessed on 1 February 2025).

Survey development

The survey instrument (Supplement: Survey Instrument) was designed by clinicians specialising in clinical psychology, psychiatry and substance use disorder. A theory of motivated behaviours, based on a brief literature review, hypothesised the relationships between mental health conditions, maladaptive behaviours and the accompanying sociodemographic and psychological covariates that guided the choice of measurement scales. The scales are highly cited and psychometrically validated from previous research. The study does not introduce novel scales. Checks for face validity and respondent comprehension were conducted on a pilot sample of 25 randomly chosen graduate students. The psychometric properties of the measurement scales were revalidated with the completed survey dataset. Item response theory was used to check for respondent bias and measurement noise.

Patient and public involvement

No patients or the public participated in the design and implementation of the study. The study employs previously validated scales. The public (general US population) was the focus of this study, and the extent of their involvement was to answer the anonymous survey questions.

Measures

The outcome variables were respondents' self-reports of consuming each of the 10 drugs listed in the clinician's Quick Screen questionnaire by NIDA-Modified ASSIST Level 2-Substance Use for Adult,[34] which screens for the use of illicit or non-medical prescription drugs, namely, prescription opioids such as fentanyl, OxyContin or methadone ('painkillers'); prescription stimulants such as Ritalin, Adderall or diet pills ('stimulants'); sedatives such as sleeping pills, Valium or Xanax ('sedatives'); cannabis such as marijuana, pot or grass ('marijuana'); cocaine', which is coke or crack; 'club drugs'; hallucinogens' such as LSD, ecstasy or mushrooms; street opioids such as heroin or opium ('heroin'); inhalants such as glue, paint thinner or nitrous oxide ('inhalants') and methamphetamine such as speed, crystal meth or ice ('methamphetamine'). Respondents indicated if they used each of the 10 drugs without a doctor's prescription during the stay-at-home order period from March to June 2020. We coded 1' for each drug that the respondent reported using. Note that we used the screening tool to measure incidences of use rather than diagnose substance use disorders since the respondents were not diagnosed by a clinician. Therefore, this study should not be read as reporting on substance use disorders in the general US population.

Respondents' self-reported demographic, social network and mobility behaviours during the stay-at-home order were measured by 10 variables. Demographics include age (age), gender (female=1), race (minority Minority status (or protected class) individuals are defined as African American, Hispanic American, Native American Indian, Asian/Pacific American, or female by the Civil Rights Act of 1991 (Public Law 102-166, United States). Individuals who are disabled, defined by the American with Disabilities Act of 1990, 42 USC § 12101), are also categorized as minority. These categories are used in the U.S. Census.=1), marital status (married or cohabit=1), children at home (household with children=1), employment status (work full time=1) and education (college and above=1). Social networks included 'Family Network', which is the sum of three items from the Lubben Social Network Scale[46] that measures the number of relatives that the respondent interacts with, feels close to and feels at ease with, and 'Friendship Network', which is the sum of three items from the same scale that measures the number of friends that the respondent interacts with, feels close to, and feels at ease with. Finally, self-reported mobility restriction behaviours were measured by how frequently respondents left their homes during the stay-at-home order to gauge the impact of the stay-at-home on mobility. This variable, 'mobility restriction', was coded 1 when the respondent reported that they never left the home, left home once a month, or left home once a week during the stay-at-home order.

Respondents reported their mental states during the COVID-19 stay-at-home order between March and June 2020. 'Trauma symptoms' were assessed using nine items

drawn from the Severity of Posttraumatic Stress Symptoms for Adults, National Stressful Events Survey PTSD Short Scale.[47 48] Respondents rated each item on a 5-point scale (0=not at all, 1=a little bit, 2=moderately, 3=quite a bit and 4=extremely). Since the Cronbach's alpha of 0.94 was high, the sum of scores from the nine items was used for analysis. 'Depression' was measured using two items from the Patient Health Questionnaire-2.[49] Respondents rated each item on a 4-point scale (0=not at all, 1=several days, 2=more than half the days and 3=nearly every day). Since the Cronbach's alpha of 0.84 was high, the sum of scores from the two items was used for analysis. 'Anxiety' was measured using seven items from the Generalised Anxiety Disorder-7 scale.[50] Respondents rated each item on a 4-point scale (0=not at all, 1=several days, 2=more than half the days and 3=nearly every day). Since the Cronbach's alpha of 0.94 was high, we used existing validated threshold scores to rate minimal (total score from 0 to 4), mild (total score from 5 to 9), moderate (total score from 10 to 14), and severe (total score from 15 to 21) levels of anxiety severity. 'Pain on most days' is a self-report dichotomous measure where 1=yes.

Statistical analysis

We ran descriptive statistics for the variables using means and SD for continuous variables and percentages for dichotomous variables. We also examined the intercorrelations among the variables and reported their significance at $p<0.05$ and $p<0.01$ (online supplemental table 1). Differences on the use of each of the 10 drugs were evaluated using χ^2 tests. We report the number and percentage of individuals who used each type of drug, the OR, 95% CI and set the level of significance at $p<0.05$. An OR below 1.0 indicates a lower likelihood of an outcome while an OR above 1.0 indicates a greater likelihood of an outcome (table 1). We used logistic regression analysis to examine the relationship between respondent demographics, social networks and mental states with each drug. We report the OR, 95% CI and p value for each of the predictor variables for each drug (table 2). We also report on the model performance statistics in terms of the Nagelkerke R^2 to assess the goodness of fit of the logistic regression model and area under (AUC) the receiver operating characteristic (ROC) curve, which measures the model's ability to correctly classify the dependent variable, so that an AUC closer to 1 represents perfect classification. Statistical analyses were performed using the Statistical Package for the Social Sciences V.28.[51]

RESULTS

The descriptive statistics and intercorrelations among the variables are reported in online supplemental table 1. Three results are notable. The correlations among the 10 drugs range from 0.47 to 0.68 and are significant at

Table 1 OR of drug use by mobility restriction

		Drug use			
Type of drug	**Leave home**	**No (n, %)**	**Yes (n, %)**	**P value**	**OR (95%CI)**
Painkiller	Once a week or less	1324, 84.3	247, 15.7	<0.001	1.57 (1.28 to 1.92)
	Once a month or never	297, 74.8	100, 25.5	<0.001	2.62 (2.03 to 3.38)
Stimulants	Once a week or less	1395, 88.8	176, 11.2	<0.001	1.56 (1.23 to 1.97)
	Once a month or never	321, 80.9	76, 19.1	<0.001	2.76 (2.08 to 3.66)
Sedatives	Once a week or less	1347, 85.7	224, 14.3	0.003	1.37 (1.11 to 1.68)
	Once a month or never	305, 76.8	92, 23.3	<0.001	2.44 (1.88 to 3.16)
Marijuana	Once a week or less	1328, 84.5	243, 15.5	0.048	1.22 (1.001 to 1.48)
	Once a month or never	308, 77.6	89, 22.4	<0.001	1.92 (1.48 to 2.49)
Cocaine	Once a week or less	1428, 90.9	143, 9.1	<0.001	1.56 (1.20 to 2.03)
	Once a month or never	326, 82.1	71, 17.9	<0.001	3.37 (2.50 to 4.54)
Club drugs	Once a week or less	1426, 90.8	145, 9.2	<0.001	1.55 (1.20 to 2.01)
	Once a month or Never	325, 81.9	72, 18.1	<0.001	3.37 (2.51 to 4.53)
Hallucinogens	Once a week or less	1415, 90.1	156, 9.9	<0.001	1.77 (1.37 to 2.30)
	Once a month or never	322, 81.1	75, 18.9	<0.001	3.48 (2.60 to 4.66)
Heroin	Once a week or less	1430, 91.0	141, 9.0	<0.001	1.64 (1.25 to 2.13)
	Once a month or never	329, 82.9	68, 17.1	<0.001	3.30 (2.44 to 4.46)
Inhalants	Once a week or less	1431, 91.1	140, 8.9	<0.001	1.56 (1.20 to 2.03)
	Once a month or never	327, 82.4	70, 17.6	<0.001	3.39 (2.51 to 4.58)
Methamphetamine	Once a week or less	1432, 91.2	139, 8.8	0.002	1.51 (1.16 to 1.97)
	Once a month or never	327, 82.4	70, 17.6	<0.001	3.37 (2.50 to 4.55)

Table 2 Logistic regression analysis of drug use among individuals who left home once a week or less

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
	Painkiller	Stimulant	Sedative	Marijuana	Cocaine	Club drug	Hallucinogen	Heroin	Inhalant	Meth
	OR (p value)	OR (p value)	OR (p value)	OR (p value)	OR (p value)	OR (p value)	OR (p value)	OR (p value)	OR (p value)	OR (p value)
Age	0.97 (0.002)	0.93 (<0.001)	0.96 (<0.001)	0.96 (<0.001)	0.93 (<0.001)	0.92 (<0.001)	0.94 (<0.001)	0.93 (<0.001)	0.94 (<0.001)	0.94 (<0.001)
Female	0.30 (<0.001)	0.27 (<0.001)	0.31 (<0.001)	0.45 (0.01)	0.26 (<0.001)	0.30 (0.001)	0.33 (0.002)	0.35 (0.01)	0.24 (<0.001)	0.32 (0.002)
Minority*	1.88 (0.04)	1.86 (0.08)	1.69 (0.08)	1.03 (0.91)	1.42 (0.36)	1.75 (0.14)	1.73 (0.14)	2.09 (0.06)	2.08 (0.07)	1.74 (0.15)
Married or cohabit	1.13 (0.71)	1.65 (0.23)	1.23 (0.53)	1.15 (0.66)	1.96 (0.16)	2.05 (0.13)	1.61 (0.28)	2.67 (0.04)	1.81 (0.22)	1.87 (0.18)
Household with children	2.94 (0.001)	2.56 (0.02)	1.98 (0.04)	2.13 (0.01)	1.78 (0.19)	2.03 (0.11)	3.01 (0.01)	2.21 (0.08)	3.47 (0.01)	3.12 (0.01)
Work fulltime	1.22 (0.55)	0.98 (0.96)	0.84 (0.58)	1.29 (0.41)	0.95 (0.91)	1.13 (0.77)	1.01 (0.99)	1.12 (0.78)	1.19 (0.69)	1.22 (0.63)
College and above	1.28 (0.43)	1.82 (0.12)	1.76 (0.07)	0.79 (0.43)	1.43 (0.39)	1.28 (0.55)	1.21 (0.64)	1.48 (0.36)	1.56 (0.30)	1.11 (0.80)
Family network	1.01 (0.89)	1.02 (0.76)	1.01 (0.80)	1.02 (0.68)	1.07 (0.33)	1.06 (0.40)	1.05 (0.51)	1.08 (0.27)	1.13 (0.10)	1.12 (0.12)
Friendship network	1.08 (0.13)	1.19 (0.002)	1.09 (0.06)	1.10 (0.03)	1.21 (0.002)	1.21 (0.003)	1.20 (0.003)	1.18 (0.01)	1.14 (0.06)	1.16 (0.02)
Trauma symptoms	1.04 (0.046)	1.02 (0.34)	1.04 (0.047)	1.02 (0.41)	1.05 (0.06)	1.05 (0.10)	1.03 (0.21)	1.05 (0.09)	1.04 (0.15)	1.03 (0.25)
Depression	1.19 (0.18)	1.41 (0.02)	1.19 (0.15)	1.30 (0.03)	1.09 (0.60)	1.27 (0.15)	1.38 (0.045)	1.31 (0.11)	1.44 (0.04)	1.30 (0.11)
Anxiety	0.99 (0.71)	0.99 (0.90)	1.02 (0.57)	0.97 (0.50)	1.01 (0.86)	0.97 (0.53)	0.96 (0.39)	0.96 (0.49)	0.94 (0.30)	0.98 (0.72)
Pain on most days	2.80 (<0.001)	3.11 (0.002)	1.48 (0.19)	2.45 (0.002)	3.31 (0.01)	4.67 (<0.001)	5.11 (<0.001)	4.12 (0.001)	5.61 (<0.001)	4.31 (<0.001)
Constant†	0.10 (0.004)	0.08 (0.01)	0.12 (0.01)	0.29 (0.08)	0.04 (0.001)	0.04 (0.002)	0.03 (<0.001)	0.02 (<0.001)	0.01 (<0.001)	0.02 (<0.001)
Nagelkerke R^2‡	43.10%	55.10%	39.40%	36.40%	53.10%	55.80%	54.90%	55.00%	58.00%	54.20%
AUC§	0.853	0.91	0.835	0.821	0.917	0.925	0.915	0.921	0.93	0.92

*Minority status (or protected class) individuals are defined as African American, Hispanic American, Native American Indian, Asian/Pacific American or female by the Civil Rights Act of 1991 (Public Law 102–166, USA). Individuals who are disabled, defined by the American with Disabilities Act of 1990, 42 USC § 12101), are also categorised as minority. These categories are used in the US Census.
†Also known as the intercept or β_0, which represents the log-odds of the outcome when all predictor variables are equal to zero.
‡This is a pseudo R^2 statistic used to assess the goodness of fit of a logistic regression model. Traditional R^2 (in linear regression) does not apply to logistic regression, so Nagelkerke R^2 provides an adjusted measure of how well the independent variables explain the variability in the dependent variable.
§AUC, which The AUC quantifies the probability that a randomly chosen positive instance is ranked higher by the model than a randomly chosen negative instance. It ranges from 0 to 1, where: AUC=0.5 suggests no discrimination (random guessing), AUC<0.5 indicates worse-than-random classification and AUC=1 represents perfect classification.
AUC, area under the curve.

p<0.01. Mobility restriction is significantly correlated with the 10 types of drugs used and range from 0.03 to 0.08. As well, the bivariate relationships between the 4 mental states and the 10 types of drugs used range from 0.20 to 0.45 and are significant at p<0.01.

Table 1 compares the differences between individuals who consumed or did not consume each of the 10 drugs using the χ^2 test. The data show those who left home once a week or less frequently during the stay-at-home order have statistically higher likelihood of consuming painkillers (OR=1.57, p<0.001), stimulants (OR=1.56, p<0.001), sedatives (OR=1.37, p=0.003), marijuana (OR=1.22, p=0.048), cocaine (OR=1.56, p<0.001), club drugs (OR=1.55, p<0.001), hallucinogens (OR=1.77, p<0.001), heroin (OR=1.64, p<0.001), inhalants (OR=1.56, p<0.001) and methamphetamine (OR=1.51, p=0.002). Table 2 also shows that those who left home even fewer times during the stay-at-home order, which is once a month or never during the 3-month period, had even higher likelihood of consuming painkillers (OR=2.62, p<0.001), stimulants (OR=2.76, p<0.001), sedatives (OR=2.44, p<0.001), marijuana (OR=1.92, p<0.001), cocaine (OR=3.37, p<0.001), club drugs (OR=3.37, p<0.001), hallucinogens (OR=3.48, p<0.001), heroin (OR=3.30, p<0.001), inhalants (OR=3.39, p<0.001) and methamphetamine (OR=3.37, p=0.002).

Table 2 reports the logistic regression used to undercover factors that are associated with each type of drug use. Model 1 shows that those who reported using painkillers were more likely to be minorities (OR=1.88, p=0.04), in households with children (OR=2.94, p=0.001), suffered from trauma (OR=1.04, p=0.046) and were in pain on most days (OR=2.80, p<0.001). Older individuals (OR=0.97, p=0.002) and being female (OR=0.30, p<0.001) were associated with lower odds of using painkillers.

Model 2 shows that those who reported using stimulants were more likely to be in households with children (OR=2.56, p=0.02), had larger friendship networks (OR=1.19, p=0.002), depression (OR=1.41, p=0.02) and pain for most days (OR=3.11, p=0.002). Older individuals (OR=0.93, p<0.001) and being female (OR=0.27, p<0.001) were associated with lower odds of using stimulants. Model 3 shows that those who reported using sedatives in non-prescribed ways were in households with children (OR=1.98, p=0.04) and reported trauma symptoms (OR=1.04, p=0.047). Older individuals (OR=0.96, p<0.001) and being female (OR=0.31, p<0.001) were associated with lower odds of using sedatives in non-prescribed ways. Model 4 shows that those who reported taking marijuana were associated with being in households with children (OR=2.13, p=0.01), had larger friendship networks (OR=1.10, p=0.03), depression (OR=1.30, p=0.03) and pain on most days (OR=2.45, p=0.002). Older individuals (OR=0.96, p<0.001) and being female (OR=0.45, p=0.01) were associated with lower odds of using marijuana.

Model 5 shows that those who reported using cocaine had larger friendship networks (OR=1.21, p=0.002) and pain for most days (OR=3.31, p=0.01). Older individuals (OR=0.93, p<0.001) and being female (OR=0.26, p<0.001) were associated with lower odds of using cocaine. Model 6 shows that those who reported using club drugs had larger friendship networks (OR=1.21, p=0.003) and pain on most days (OR=4.67, p<0.001). Older individuals (OR=0.92, p<0.001) and being female (OR=0.30, p=0.001) were associated with lower odds of using club drugs. Model 7 shows that those who reported using hallucinogens were associated with being in households with children (OR=3.01, p=0.01), had larger friendship networks (OR=1.20, p=0.003), depression (OR=1.38, p=0.045) and pain on most days (OR=5.114, p<0.001). Older individuals (OR=0.94, p<0.001) and being female (OR=0.33, p=0.002) were associated with lower odds of using hallucinogens.

Model 8 shows that those who reported using heroin were married or in a cohabiting relationship (OR=2.67, p=0.04), had larger friendship networks (OR=1.18, p=0.01) and pain on most days (OR=4.12, p=0.001). Older individuals (OR=0.93, p<0.001) and being female (OR=0.35, p=0.01) were associated with lower odds of using heroin. Model 9 shows that those who reported using inhalants were associated with being in households with children (OR=3.47, p=0.01), had depression (OR=1.44, p=0.04) and pain on most days (OR=5.61, p<0.001). Older individuals (OR=0.94, p<0.001) and being female (OR=0.24, p<0.001) were associated with lower odds of using inhalants. Finally, model 10 shows that those who reported using methamphetamines were associated with being in households with children (OR=3.12, p=0.01), had larger friendship networks (OR=1.16, p=0.02) and pain on most days (OR=4.31, p<0.001). Older individuals (OR=0.94, p<0.001) and being female (OR=0.32, p=0.002) were associated with lower odds of using methamphetamine.

DISCUSSIONS

Bivariate correlations indicate that consumption of the 10 drugs was related, suggesting that they tend to be consumed together. Comparisons between those who reported taking drugs and those who reported that they did not show that those who went out no more than once a week during the stay-at-home order had a higher likelihood of consuming drugs. The likelihood of taking drugs was even higher for those who went out only once a month or never went out during the stay-at-home order. Separately, we explored the frequency of polydrug use in a supplemental analysis, showing that among the 25% of the general population reporting drug use, half used more than one type of drug (online supplemental table 2).

Logistic regression analysis revealed the factors that were associated with drug use among those who experienced mobility restrictions during the stay-at-home order and rarely left their homes. Specifically, trauma symptoms, depression or pain on most days were mental states that were associated with higher odds of drug use. Individual profiles related to having children at home

were associated with higher odds of drug use, which is in line with studies that noted that increased burdens in childcare and homeschooling responsibilities due to the forced closure of childcare facilities and schools caused significant psychological distress among adults with children at home.[4]

Those with a larger network of friends were also associated with higher odds of drug use, which is in line with studies that suggest higher use of recreational drug consumption among friends.[36 39 41 42 44] That being female was associated with a lower likelihood of drug use was similar to reports that indicate that men were more likely than women to use all types of illicit drugs.[45] Adults with children at home—where women were primarily the caregivers—were associated with higher risks of drug use. However, women also reported lower drug use, which may seem contradictory. This is not the case because our regression model estimated the independent effects of each variable, and the category of adults with children at home included both men and women. Finally, older individuals were associated with a lower likelihood of drug use, which adds to past findings that found no consistent changes in drug use for older persons.[43] Overall, our results support past studies. However, past studies did not link the incidence of drug use to social isolation and mental states due to the COVID-19 mobility restriction, which we do in this paper.

This study is subject to the usual limitations. First, the stay-at-home period was imposed federally for an initial 6 weeks and then extended for several more. Not all states rigorously imposed their stay-at-home measures during the extended period. For example, after the initial 6 weeks, New York State and California continued to implement strict stay-at-home policies whereas Florida, Arizona and Texas were more relaxed in their enforcements. Our study does not account for the heterogeneity of stay-at-home measures during the extended period. That said, we asked respondents to indicate the extent to which they stayed at home during the stay-at-home order to measure their mobility. Second, we implemented our survey in June 2020, which is 3 months after the Federal stay-at-home order in March 2020. Three months is not long enough to demonstrate the long-term consequences of stay-at-home orders on drug use. This aspect of the COVID-19 pandemic continues to be an unfolding story and deserves more study in the years to come.[52] We chose to implement our survey 3 months after the stay-at-home order to be sure that the self-reports on mental health and behaviours are proximate to the event (stay-at-home order) and to mitigate against recall inaccuracy and recall bias. We also acknowledge the usual limitations of using a survey. For example, the online survey responses were self-reports. Since the survey collected only cross-sectional data, we could not determine causality between the predictor and outcomes. Pain was measured by a single item, which is routinely used in the clinic, and as such we could not report reliability statistics. The respondents were not interviewed and diagnosed by a clinician to determine whether they met the thresholds of various mental state disorders. As such, there may be confounding effects from using drugs because of substance use disorder vs recreationally. In this regard, we strongly caution that our study should not be read as a clinical study of drug use in the population. Hence, our results should not be taken as clinical practice guidelines with diagnostic or therapeutic value. This said, our survey employed well-validated and widely used scales, and our data suggested representativeness of the general US population, supported by the usual statistical diagnostics for data error or non-compliant distributions.

CONCLUSIONS

The purposes of this study are to explore drug use during the COVID-19 stay-at-home order in the USA and to determine the extent to which mobility behaviours, demographics, social networks and mental states may be associated with drug use. In a sense, our results should be unsurprising to thoughtful observers of the pandemic, as early observations such as the survey by the US Substance Abuse and Mental Health Services Administration (SAMHSA) and other organisations provided some clues on the likely effects.[53]

In terms of future research, our survey reports that polydrug users comprised 12.5% of our survey population, suggesting that future research could focus on the phenomenon of polydrug use in the general population during times of general stress (Supplement Table 2). Further, we discussed understanding maladaptive consumption behaviours during periods of general stress in the introduction. We focused on drug use in this study, yet there are other forms of addiction such as online gambling, sex, food and alcohol. We feel that future research can focus on the phenomenon of addiction switching or the replacement of one type of behaviour with another to explore a deeper level of complexity in this phenomenon.

While the effects of COVID-19 on school-going children and young adults have been reported elsewhere,[38 39 41 42] the effects of the COVID-19 stay-at-home order on adult drug consumption behaviours are less well documented. Our survey reports that those who were more mobility restricted were also more likely to use drugs. This begs the question, how did individuals obtain their drugs? We know that regular users of illicit drugs have established primary sources of supply comprising organised crime networks and local dealers that supply through in-person transactions and home delivery,[54] while non-medical users of prescription drugs obtain supplies from anonymous online drug marketplaces or via diverted sources.[55 56] The volume of online shopping increased five times during COVID-19, suggesting that it became a major supply chain channel for goods.[57] Future research can explore the drug supply chain during periods of widespread crisis for the purpose of designing pre-emptive interventions.

From a policy standpoint, we show in this study that the effects of public health mandates are not equally distributed among the population and that specific consideration must be given to vulnerable groups such as families with school-going children. For policy-makers, this means that future infection control measures that require extended social isolation will need adjuvant interventions to mitigate the increased mental health concerns that follow.[58 59] Technology-enabled interventions, using social media, virtual networking and gaming technology, many of which took off during the pandemic, offer potential solutions for wide deployment in the population. Befriending programmes using virtual meeting technology, which can be facilitated by civil society organisations, can also help.[60] These interventions should be rolled out proactively, together with the infection control measures, since, as our data show, the mental health conditions leading to maladaptive behaviours can set in quickly. Future interventional studies could take the form of social support groups for people with children at home, and age-targeted entertainment options through public broadcasters to mitigate the effects of fear, anxiety and depression associated with social isolation.

Public health experts should do well to reflect on the immediate and long-term consequences of infection control in the care of people with drug use disorders. For example, healthcare providers and policy-makers experimented with strategies to maintain continuity of care. Regulatory agencies temporarily relaxed restrictions on medications for opioid use disorder (MOUD), such as allowing take-home methadone and expanded prescribing of buprenorphine via telemedicine.[28] These policy experiments highlighted the potential for more flexible treatment models beyond the pandemic era, with early evidence suggesting that expanded access to MOUD can significantly improve treatment retention and reduce overdoses.[26] More critically, such strategies can inform financing policy decisions that must ultimately be crafted to support care provision. Finally, a worrisome trend is the accelerating volume of new psychoactive substances (NPS) such as fentanyl (anaesthetic) and xylazine (large animal tranquilliser) in the illicit drug supply that makes screening and detection challenging.[61] Substance users are often unaware of the presence of such diluents in their drugs of choice. In a national health emergency, the delay in detection and treatment for NPS-related morbidity will inevitably lead to higher mortality and healthcare costs. Policy-makers would do well to prioritise resources for solving (from detection to intervention) this growing problem.

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