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Smoking rates among those who use prescribed or recreational opioids are significantly higher than the general population. Hypothesized neuropharmacological interactions between opioids and nicotine may contribute to this pattern of polysubstance use, especially during withdrawal. However, little research has examined how the withdrawal of one substance may affect the consumption of the other (i.e., cross-drug withdrawal effects). Behavioral economic demand tasks (e.g., hypothetical purchase tasks) can be used to quickly assess the value of a drug. Crowdsourcing can be a convenient tool to gain preliminary insight into different processes in substance valuation that may otherwise be impossible or prohibitively difficult to study. The purpose of the present study was to provide a preliminary examination of the effects of hypothetical withdrawal of cigarettes and opioids on the consumption of those drugs among polysubstance users. Amazon Mechanical Turk workers who reported daily smoking and at least monthly opioid use completed a series of hypothetical purchase tasks for doses of opioids and cigarettes under various withdrawal conditions. Sensitivity to the price of both drugs decreased when under withdrawal for either, indicating a higher drug value of cigarettes and opioids due to effects of cross-drug withdrawal. Nicotine and opioid dependence severity, impulsive choice, and riskiness were also positively related to drug purchasing.

Public Health Significance

The results of this study suggest that opioid withdrawal may increase the value of cigarettes and therefore difficulty in quitting smoking, while nicotine withdrawal may similarly increase the value of opioids and difficulty in quitting opioid use. Results of this study could inform treatment development by explaining difficulties in maintaining abstinence that may arise as a function of cross-drug withdrawal effects between opioids and nicotine.

Keywords: behavioral economics, opioid use, cigarettes, withdrawal

Supplemental materials: https://doi.org/10.1037/pha0000558.supp

While smoking and opioid use individually pose health risks, the frequent comorbidity of smoking and opioid can result in additional negative health outcomes, as smokers with comorbid substance use have higher mortality rates than nonsmokers (e.g., Bandiera et al., 2015; Hser et al., 1994). In the United States, those who use opioids are roughly four times more likely to smoke than the general population with studies estimating approximately 80% smoking rates in this population (Parker et al., 2018; Rajabi et al., 2019). Both

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drugs carry significant health risks and constitute a significant burden on the United States healthcare system (Hsu et al., 2017; Xu et al., 2015). Concurrent cigarette smoking during opioid detoxification increases subjective feelings of opioid withdrawal (Mannelli et al., 2013), and opioid users are less likely to successfully quit smoking cigarettes (Parker et al., 2020) than nonopioid users. This could be due in part to interactions between nicotine and opioids (Yoon et al., 2015). One possible explanation for this is that use of one drug may alleviate withdrawal symptoms of the other. For example, smokers with opioid use disorder tend to experience lower subjective cravings when attempting to quit smoking while on buprenorphine or methadone (Mannelli et al., 2013). However, another possible explanation is that there is an interaction between opioids and nicotine, in which opioid use will increase smoking (Mello et al., 1980, 1985). Similarly, nicotine use appears to increase the value of opioids, as cigarette smoking will increase consumption of methadone compared to those abstaining from cigarettes (Spiga et al., 1998, 2005). Sex may also contribute to differential effects, as females report higher subjective withdrawal to opioids than males (Huhn et al., 2019), which in turn could lead to worsened outcomes for cigarette-smoking females seeking treatment for opioid use. Unfortunately, current data on sex-based differences in treatment outcomes for opioid use is mixed (Huhn et al., 2019).

Due to these cross-drug effects, there have been calls for treating both nicotine and opioid use simultaneously rather than individually (Morris & Garver-Apgar, 2020). Moreover, a meta-analysis by Prochaska et al. (2004) and updated narrative review by McKelvey et al. (2017) found that smoking cessation during other substance use treatments had either no effect or a beneficial effect on long-term treatment outcomes. Even though there is high co-use of nicotine and opioids, there is relatively little research investigating how withdrawal effects associated with one affect the consumption of the other (i.e., cross-drug withdrawal effects), which is an important factor to consider given the goal of decreasing use of either drug. Because of the complex and at times contradictory relationship between opioid and nicotine use during cross-drug withdrawal, more research is needed to clarify what factors may contribute to drug use to better identify ways that cross withdrawal will affect drug use. Such findings could lead to improvements in drug treatment programs to decrease relapse that may be a result of complex behavioral or neurochemical processes between nicotine and opioids.

Determining Drug Value

One way the relationship between nicotine and opioid use can be quantified is via *behavioral economic demand* (hereafter, demand; see Koffarnus & Kaplan, 2018). Briefly, demand is the study of how an organism works for and consumes a specific commodity under various constraints. The original terminology foundational to the study of demand was adopted from economic theory by Hursh (1980, 1984) to allow for a quantitative analysis of behavior while also maintaining conceptual ties to the experimental analysis of behavior. This framework has been extended to numerous subject areas, with notable utility in substance use research (e.g., Aston & Cassidy, 2019; Koffarnus & Kaplan, 2018). While there are several metrics that have been used in the analysis of demand (see Bickel et al., 2000), the two metrics that will be emphasized here are intensity and sensitivity to price (i.e., change in elasticity). Intensity refers to the amount of a commodity, such as cigarettes, that one would consume in a particular period (e.g., a day, an hour) if the cost of that commodity was free. Change in elasticity refers to the sensitivity of consumption to increasing effort or cost of said commodity. Because of inconsistent use of the term elasticity,[1] we discuss changes in consumption as a function of increasing price as either sensitivity to price or how consumption of a commodity is defended as price increases. Defending a commodity refers continuing to expend money or effort to maintain a similar level of consumption of or access to a commodity even as effort or cost to the organism increases. Sensitivity to price is considered an important factor in demand as it relates to how much effort an organism will exert for a commodity, and a metric of the value of that commodity (Hursh & Silberberg, 2008). Generally, as cost or effort for a commodity increases, demand for and consumption of that commodity decreases. Consumption that quickly decreases as price increases is considered relatively sensitive (sometimes called elastic), whereas consumption that maintains or decreases at a slower rate across increases in price is considered relatively insensitive (sometimes called inelastic). Higher intensity and lower price sensitivity are associated with greater severity of smoking (González-Roz et al., 2019) and alcohol use (Kiselica et al., 2016). While there have been studies that use real effort and consumption of nicotine or opioids (Petry & Bickel, 1999; Spiga et al., 2005), many studies use a *hypothetical purchase task* (hereafter, purchase task; e.g., Higgins et al., 2017; Jacobs & Bickel, 1999; MacKillop et al., 2012; Strickland et al., 2019; see Strickland et al., 2020 for a review).[2] Purchase tasks are often pen and paper or computerized tasks that involve a vignette (assumptions about the hypothetical situation to control for covert verbal behavior, such as assuming there is no access to other drugs other than those available in this task) and asking a participant how much of a commodity (e.g., cigarettes, opioid doses) they would consume at various costs. These responses can then be used to extract relevant demand metrics. In substance use research, these demand metrics have been shown to relate to validated instruments and are predictive of relevant clinical outcomes. For example, a meta-analysis of cigarette demand studies (González-Roz et al., 2019) found that the Fagerström Test for Nicotine Dependence (FTND; Heatherton et al., 1991) is positively correlated with intensity (i.e., base consumption increased) and negatively correlated with sensitivity to price. Other studies have found that intensity (González-Roz et al., 2020; Yoon et al., 2020) and sensitivity to price (González-Roz et al., 2020; Schwartz, Blank, et al., 2021; Secades-Villa et al., 2016) assessed via purchase tasks correspond with likelihood of drug relapse and abstinence. A recent meta-analysis also found that purchase tasks are also sensitive to manipulations such as interventions or hypothetical contexts (Acuff et al., 2020).

Purpose

Because of the comorbidity of nicotine and opioid use and the respective challenges of their co-use in achieving abstinence of either drug, understanding how withdrawal for one drug may affect use of the other could be relevant to substance use treatment.

[1] See Gilroy et al. (2020) for detailed discussion on elasticity.

[2] For a more general overview of the development and applications of purchase tasks outside of substance use, see Roma et al. (2017).

Understanding these drug withdrawal interactions could also shed insight into maladaptive patterns of substance use. Crowdsourcing can provide useful preliminary steps to explore hypotheses to better understand how various manipulations may affect polysubstance use. Of the crowdsourcing methods, Amazon Mechanical Turk (MTurk) has been used extensively in psychological and addiction research (Mellis & Bickel, 2020; Strickland & Stoops, 2019). Using purchase tasks in conjunction with crowdsourcing methods can be a practical first test to determine potential effects of future experimental manipulations or provide insight into processes that may contribute to other observer phenomena. Therefore, the purpose of this study was to assess how demand for nicotine and opioids is affected based on withdrawal for either drug. We hypothesized that withdrawal for either drug would increase intensity and decrease price sensitivity (i.e., consumption is more likely to be defended/continued consumption at higher prices) for both drugs relative to baseline conditions.

Method

Recruitment

Participants were recruited from Amazon Mechanical Turk (MTurk). To access the study, participants needed to (a) be located in the U.S., (b) have completed ≥50 human interface tasks (HITs), and (c) have ≥90% HIT approval. These are similar values that have been used in previous research in substance use on MTurk (e.g., Cunningham et al., 2017; Morris et al., 2017; Strickland et al., 2019). After beginning the survey, participants were required to complete a brief screener for eligibility, followed by an attention check and a CAPTCHA (to screen out bots). To be included in the study, participants must also have endorsed daily cigarette use within the past year and monthly prescription or nonprescription opioid use within the past year. Ineligible participants were excluded from the study and the survey was ended. Compensation for completing the study was $7.50 based on an expected time to completion of 45 min. The experimental survey was posted on MTurk in Fall of 2019. Procedures for this study were approved by the Virginia Tech Institutional Review Board, IRB #19-431, "Decision making of commodities using crowdsourcing." This study was not preregistered and because of the exploratory nature of the study, the sample size was not predetermined.

Hypothetical Purchase Tasks, Monetary Discounting, and Demographics

While participants completed other tasks, only purchase tasks related to opioid/cigarette consumption, consumption during withdrawal, and monetary discounting are reported here. Prior to the baseline cigarette purchase task, participants were asked questions regarding the usual brand of cigarettes they smoke and their cost. The same was done for opioids, in which participants identified the usual type of opioid used and the cost of a single dose. The order of purchase task (i.e., cigarette or opioid) was randomly presented. Purchase tasks consisted of a series of questions with ascending prices as well as a preamble instructing participants to imagine that any drug purchased can only be consumed within a 24-hr period, they had no obligations the next day, and the purchased drugs could not be sold or saved. These assumptions are in line with recommended practice for constructing purchase tasks (Kaplan et al., 2018; Reed et al., 2020). For individual cigarettes, the prices were $0.00, $0.01, $0.05, $0.10, $0.25, $0.50, $1, $2, $5, $10, $25, $50, $100, and $200. For individual doses of opioids (defined as their usual dose consumed), the prices were $0.00, $0.01, $0.05, $0.10, $0.25, $0.50, $1, $2, $5, $10, $25, $50, $100, $200. $400, $800, and $1,600. Prices were presented individually (i.e., 1 price point per survey page). An example question of the baseline cigarette purchase task is "How many of your usual brand cigarettes would you purchase and consume if the cost was $0.05 (5 cents) per cigarette?"

After completing both baseline purchase tasks, participants were presented with vignettes on cigarette withdrawal and opioid withdrawal prior to beginning the respective withdrawal condition. For example, "For the following questions, imagine you have not used [Chosen Opioid] for some time and now are in withdrawal from opioids. Imagine that you are experiencing the following feelings related to your withdrawal: Anxiety, body aches, tiredness, chills, and nausea.," where [Chosen Opioid] was replaced with the type of opioid participants reported using most. They were then asked to also briefly describe some of their feelings while going through withdrawal to increase the salience of the withdrawal purchase tasks immediately following the withdrawal vignettes. Participants then completed withdrawal purchase tasks for both cigarettes and opioids. The assumptions presented prior to a withdrawal consumption condition were the same as described above but with the inclusion that they were in withdrawal from opioids or cigarettes. These were presented in random order (i.e., either cigarettes first or opioids first) as well as random order of cigarette or opioid withdrawal conditions within a specific drug consumption condition. An example question for cigarette purchasing under the opioid withdrawal condition was "Imagine you are in withdrawal from opioids. How many of your usual brand cigarettes would you purchase and consume if the cost was $0.50 per cigarette?." The full vignettes of the purchase tasks and more example questions can be found in the Supplemental Materials under the Purchase Task Vignettes section. Therefore, there were a total of six drug demand purchase tasks in total: Baseline cigarette and opioid demand, cigarette withdrawal for cigarette and opioid demand, and opioid withdrawal for cigarette and opioid demand. Prior to each purchase task, participants were required to correctly answer comprehension check questions following each instruction page before being able to advance. The checks consisted of a multiple-choice question such as "Based on the instructions you read above, what are you to imagine you will be purchasing?" or "Based on the instructions you read above, what are you to assume when purchasing in the following questions?."

Following completion of the purchase tasks, participants completed the 5-trial discounting task (Koffarnus & Bickel, 2014; Koffarnus et al., 2021) for delay and probability discounting at two magnitudes ($100 and $1,000). Briefly, these tasks consist of five questions each and estimate a single value for self-control (i.e., delay discounting k) or risk aversion (i.e., probability discounting h). Higher k values are thought to be indicative of lower self-control (i.e., preference for the smaller *sooner* option), whereas higher h values are thought to be indicative of lower propensity for risk-taking (i.e., preference for the smaller *certain* option). Participants are asked to choose between an immediate/certain choice at half the value of a delayed/uncertain choice. For example, the $1,000 delay

condition starts with "Which would you rather have: $500 now or $1,000 in 3 weeks?" whereas the $100 probability condition starts with "Would you rather have: $50 for sure or $100 with a 50% chance." Based on the choice, the delay or probability would either increase (larger option was chosen) or decrease (smaller option was chosen). The benefit of using this type of monetary discounting task is in its time to complete and correlation with more time-consuming discounting measures. See Koffarnus and Bickel (2014) for more details of the delay variant of the 5-trial discounting task and Koffarnus et al. (2021) for more information on the probability variant. Monetary discounting was included because of its relationship with substance use, where higher values of k (i.e., lower self-control) are related to increased substance use (Amlung et al., 2017). Participants also completed basic demographic questions and questions related to drug use. These included the FTND (Heatherton et al., 1991), and the DSM 5 Criteria for Opioid Use Disorder (DSM 5 OUD; American Psychiatric Association, 2013). Materials are available upon request.

Data Analysis

Prior to analysis, if any participant responded with consuming more than 200 cigarettes or 50 doses of their chosen opioid within a 24-hr period, that participant's data were removed from all subsequent analyses. These exclusion criteria were chosen because they represented an impossible number of cigarettes or opioid doses (i.e., not physically smokable in a day or lethal doses of opioids) that could be consumed within a 24-hr period. Qualitative responses to imagined feelings of withdrawal were checked to determine potential low-quality responding (e.g., copy-pasted answers, one-word answers such as "no"). While data paths were assessed for unsystematic responding (Stein et al., 2015), no data were removed based on systematicity prior to model fitting. We chose to include these data sets because the mixed-effects modeling approach is generally robust against these types of data trends (e.g., mixed-effects models leverage information about how others in the sample respond and incorporates this information into determining group-level parameter estimates) assuming the proportion of unsystematic response sets are relatively minimal. However, to determine if inclusion of unsystematic data affected results, a secondary analysis was conducted as part of best practice for model evaluation. To assess demand, the exponentiated model of demand (Koffarnus et al., 2015) was applied to all data sets using mixed-effects modeling (Kaplan et al., 2021). The exponentiated model of demand is

$$Q = Q_0 \times 10^{k(e^{-\alpha Q_0 C}-1)}. \quad (1)$$

In the exponentiated model, Q represents consumption at a given cost, C represents a given cost, Q_0 represents the consumption of a drug at no cost (i.e., intensity), α represents the change in elasticity for a commodity (i.e., lower α indicates consumption defended as price increases), and k represents the span parameter.[3] In our analyses, Q_0 and α were treated as fitted parameters to be estimated whereas k was a constant determined a priori based on the empirical data. The exponentiated model has been successful at describing demand curves and is able to incorporate zero-consumption values without modification (Koffarnus et al., 2015).

To implement the mixed-effects modeling of demand data, analyses were conducted in R (R Core Team, 2020) using the *nlme* (Pinheiro et al., 2020), *beezdemand* (Kaplan et al., 2019), *emmeans* (Lenth, 2020), and *tidyverse* (Wickham et al., 2019) packages. There are three main benefits of mixed-effects modeling compared to other methods of modeling demand data (fitting to means or fitting a single curve to each participant). First, mixed-effects modeling fits all data simultaneously and accounts for the within-subject nature of purchase task data. Participant-level predictions are treated as random effects, which are represented as deviations (relatively higher or lower) from the sample's fixed effects (group-level estimates). Second, as mentioned earlier, unsystematic data that otherwise may be excluded (Stein et al., 2015) can be included in the analysis. Third, mixed-effects modeling can incorporate conceptually relevant variables to be estimated along with the free parameters from the demand equation, allowing for direct assessment of the relation of demographic variables (e.g., sex, self-reported substance use) with estimates of Q_0 and α. For an introduction to mixed-effects modeling for demand curve data, see Kaplan et al. (2021) and for single-subject data, see DeHart and Kaplan (2019).

For each drug, there were two different models used to assess demand data. The first was agnostic of any covariates and only used the consumption data from the different withdrawal conditions. The second included variables that were theoretically relevant to the purchase tasks such as the FTND, DSM 5 OUD, and sex. For both the FTND and DSM 5 OUD the raw total scores were used to estimate the relationship between these validated instruments and their relationship with demand metrics. Due to reported sex differences regarding opioid withdrawal (Huhn et al., 2019), a model with main effect of sex assigned at birth on Q_0 and α as well a model with interactions between sex and condition were also conducted. The k span parameter was determined for each drug, one for cigarettes and one for opioids using the *GetK* function from the *beezdemand* package (Kaplan et al., 2019), which determines k empirically from the $\log_{10}$ mean range of consumption +0.5. A constant was added to the span parameter (the default calculation for k in the *beezdemand* package), which can allow for the model to more closely approximate 0 levels of consumption (see Gilroy, 2022). Drug specific k parameters were used because the consumption for cigarettes was substantially higher than doses of opioids and a distinct k for each drug would allow for appropriate comparisons between withdrawal conditions within a drug. Also, because the consumption of drugs was not being directly compared—only withdrawal conditions within a drug type were compared—a shared k across drugs was not required. Data are available upon request.

Mixed-Effects Modeling Process

Nonlinear regression requires starting (i.e., initial) values to begin parameter estimation. To help aid with nonconvergence issues, the formula in Equation (1) was converted to

$$Q = 10^{Q_0} \times 10^{k(e^{-10^{\alpha} 10^{Q_0} C}-1)}, \quad (2)$$

where Q_0 and α are fit in $\log_{10}$ space by exponentiating all parameters to be estimated. Equation (2) is mathematically the same as Equation (1), but we have found that estimating parameters

[3] Note that this k parameter is unrelated to the k parameter for delay discounting.

in this way using mixed-effects models decreases convergence issues and fitting the data using (2) resulted in better AIC and log-likelihood values relative to fitting the data with (1). Because of this, all values of Q_0 and α are presented in $\log_{10}$ units. To further aid in model fitting, there was a three-step process used to help identify optimal start values for parameter estimation. For the first step, a nonlinear least squares regression model fit to all the data within a drug class (i.e., nicotine or opioids) was used to estimate Q_0 and α. These values were then used as start values for generalized nonlinear least squares model that included the fixed effects of withdrawal conditions. This in turn produced updated estimates for Q_0, α, and withdrawal conditions relative to baseline. These estimates were then used in the mixed-effects model as start values for the fixed effects being estimated. A blocked random-effects covariance matrix was specified with a symmetric covariance matrix of Q_0 and α for participant and a diagonal covariance matrix of Q_0 and α for withdrawal condition. For more details of the use of mixed-effects models for behavioral economic demand, see Kaplan et al. (2021), as well as the Supplemental Materials Documents: Code section for how the models were specified. This same process was used for the mixed-effects models that included the FTND and DSM 5 OUD. FTND and DSM 5 OUD scores were mean centered and scaled during the regression analysis. This was to standardize the estimates to foster relative comparisons between them. Main results are derived from the model that includes covariates, however the base (i.e., no covariates) model was used to graph demand curves and for correlations described below. Because all estimates of Q_0 and α were estimated in $\log_{10}$ units, all regression estimates, effects of covariates, and differences in fixed effects can be interpreted as proportional differences or changes.

The mixed-effects models were also assessed based on the accuracy of estimating consumption at \$0. This was done by extracting the random-effects predictions for Q_0 from each participant from the base model and then comparing against observed consumption of cigarettes and opioid doses at all conditions at \$0 per unit of drug. To further validate results of fixed effects included in the covariate model, all random-effect predictions of α were also extracted from the base model, and then Q_0 and α for each condition and drug were correlated with factors included in the covariate model as well as monetary discounting. This was done because of collinearity between discounting measures and as analogous to methods used in traditional two-stage analyses. Calculations of within-subject effect sizes were done by taking the difference between two conditions and dividing the mean difference by the standard deviation of difference scores (i.e., Cohen's d_z). This approach was used rather than the built-in function *eff_size* in the *emmeans* package because it was not clear given the complexity of the models how to determine standard deviation while accounting for the repeated measures nature of the study.[4] Exact model specifications, code used for the analysis, and additional outputs can also be found in the Supplemental Materials Documents: Code section.

Results

Participants, Demographics, and Exclusions

A total of 244 participants were eligible based on reported opioid and cigarette use and were filtered into the study. Median time to survey completion was 49.8 min, indicating a median compensation of \$9.03/hr for the total survey. Most participants were male (63.5%), Caucasian (73.4%), and had at least a 4-year degree (53.2%). Complete demographics can be found in Table 1. Based on qualitative responses to imagined withdrawal symptoms, there were 13 participants who may have had suspect (i.e., potentially inattentive or insincere) data quality. Following exclusion of participants who reported consuming ≥200 cigarettes or ≥50 opioid doses, 178 participants were retained for purposes of demand analysis, six remained of the 13 that may have had suspect data quality. These data were retained because it was a relatively small subset of the remaining participants, although an analysis was conducted that removed these six participants (see Footnote 5). No other exclusion criteria were applied for demand analyses. Comparisons of demographics of those removed based on these criteria are available in Supplemental Materials Table S1. The counts and percentages of unsystematic response sets based on the Stein et al. (2015) criteria for the data included in the study (n = 178) can be found in Supplemental Materials Table S2. No data were excluded based on Stein et al. (2015) criteria and frequencies are only reported for posterity. There were 35 unique participants that met at least one of the unsystematic criteria over all six conditions, primarily in the ΔQ criteria. Notably, ΔQ criteria failures were highest for cigarettes in the nicotine withdrawal condition (9.6%) and for opioids in the opioid withdrawal condition (12.4%). Failures of ΔQ were lowest in baseline conditions for cigarettes (3.4%) and opioids (5.1%). There were no bounce criteria failures, and only one reversal failure for opioids in the baseline and opioid withdrawal conditions. Analyses excluding participants who had any unsystematic data are available in the Supplemental Materials to verify the performance of the mixed-effects modeling procedure. An alternative analysis that excluded the remaining six suspect participants (i.e., the remaining suspect participants from the original 13 not excluded via the consumption threshold) was conducted and compared to the main analysis. Because there were no changes in significance or direction of results based on removing these six participants, these data are not reported.

Cigarette Demand

Predicted demand curves from the base model for cigarette consumption under each withdrawal condition (baseline, cigarette withdrawal, and opioid withdrawal) are shown in Figure 1. Fits to group data and individual fits from the random-effects predictions can be found in the Supplemental Materials Figures (Figures S1–S5). Table 2 (left side) displays the regression output from the covariate model that only includes main effects, as sex by condition interactions did not meet statistical significance (all other regression outputs, analyses, and contrasts not described here can be found in Supplemental Materials Tables S3–S8). Higher scores for nicotine dependence (FTND) were associated with higher Q_0 and lower α. Higher scores in the DSM 5 OUD were associated with lower α, indicating greater opioid use severity was associated with a lower sensitivity to price for cigarettes. Sex was not significantly related to cigarette demand.

[4] The author of the emmeans package has also debated on whether standardized effect sizes are appropriate for mixed effects models.

Table 1
Demographics of Study Sample

Participant characteristic	Total/Mean	*SD*/%
N	244	100%
Age	32.89	±8.53
Gender (%)		
Man	155	63.5%
Woman	85	34.8%
Transgender	4	1.6%
Race		
American Indian or Alaska Native	4	1.6%
Asian Indian	4	1.6%
Black or African American	37	15.2%
Chinese	4	1.6%
Filipino	3	1.2%
Guamanian or Chamorro	1	0.4%
Japanese	1	0.4%
Korean	3	1.2%
Other	4	1.6%
Other Asian	1	0.4%
Vietnamese	3	1.2%
White/Caucasian	179	73.4%
Incomes		
$0 to $24,999	19	7.8%
$25,000 to $49,999	79	32.4%
$50,000 to $74,999	69	28.3%
$75,000 to $99,999	47	19.3%
$100,000 to $149,999	23	9.4%
$150,000 to $199,999	4	1.6%
$200,000 or more	3	1.2%
Ethnicity (%)		
No, not of Hispanic, Latino, or Spanish origin	217	88.9%
Yes, Cuban	1	0.4%
Yes, Mexican, Mexican American, Chicano	24	9.8%
Yes, Puerto Rican	2	0.8%
Education (%)		
Less than High School	0	0%
High School/GED	30	12.3%
Some College	59	24.2%
2-Year College Degree	25	10.2%
4-Year College Degree	78	32%
Master's Degree	45	18.4%
Doctorate	2	0.8%
Professional Degree	5	2%
Employment (%)		
Employed full-time	187	76.6%
Employed part-time	37	15.2%
Retired	1	0.4%
Unemployed	19	7.8%
Nonprescription Opioid Use	150	61.5%
FTND		
Overall Mean	4.28	±2.8
Very low (0–2)	62	25.4%
Low (3–4)	62	25.4%
Moderate (5)	27	11.1%
High (6–7)	56	22.9%
Very High (8+)	37	15.2%
DSM 5 self-reported OUD		
Overall Mean	6.1	±4.0
No disorder (0–1)	41	16.8%
Mild (2–3)	25	10.3%
Moderate (4–5)	36	14.7%
Severe (6+)	142	58.2%

Note. Totals or means of demographics. For continuous variables, *SD* is in the right column. For categorical variables, % is in the right column. FTND = Fagerström Test for Nicotine Dependence total score, ranges from 0 to 10. DSM 5 OUD = Total score from the DSM 5 criteria for opioid use disorder, ranges from 0 to 13. Overall mean as well as bins based on nicotine dependence severity and opioid use severity are presented.

Figure 2 shows the estimated coefficient values of Q_0 and α for cigarette consumption based on withdrawal condition. Post hoc comparisons of Q_0 indicated significantly lower values under nicotine withdrawal compared to opioid withdrawal, $t(7,293) = 3.16$, $p = .006$, $d_z = -0.278$, and Q_0 under nicotine withdrawal being lower than baseline, $t(7,293) = 2.16$, $p = .076$, $d_z = -0.172$. For α, differences between baseline and cigarette withdrawal, $t(7,293) = 9.31$, $p < .001$, $d_z = 0.364$, and baseline and opioid withdrawal, $t(7,293) = 6.99$, $p < .001$, $d_z = 0.343$, were significant, which suggests that sensitivity to price for cigarettes was lower under both forms of withdrawal. Furthermore, α was significantly lower in the opioid withdrawal condition relative to the nicotine withdrawal condition, $t(7,293) = 2.381$, $p = .039$ $d_z = -0.072$. A visual comparison between the estimated coefficients from the base model and covariate model can be found in Supplemental Materials Figure S6. Table 2 contains raw differences and effect sizes for Q_0 and α for cigarette consumption controlling for covariates.

Opioid Demand

Predicted demand curves for opioid consumption under each withdrawal condition (baseline, cigarette withdrawal, and opioid withdrawal) are shown in Figure 3. Fits to group data and individual fits from the random-effects predictions can be found in the Supplemental Materials Figures S6–S11. Similar to the cigarette demand analysis, no significant interaction between sex and condition was observed. Table 2 (right side) contains the regression outputs from the covariate model for opioid demand. Higher scores for DSM 5 OUD were associated with higher Q_0 values and lower α values. Higher FTND was associated with lower α values, suggesting that greater nicotine dependence was associated with lower sensitivity to price for opioids. Model outputs from the other regressions, contrasts, and analyses not described here can be found in the Supplemental Materials Tables S9–S14.

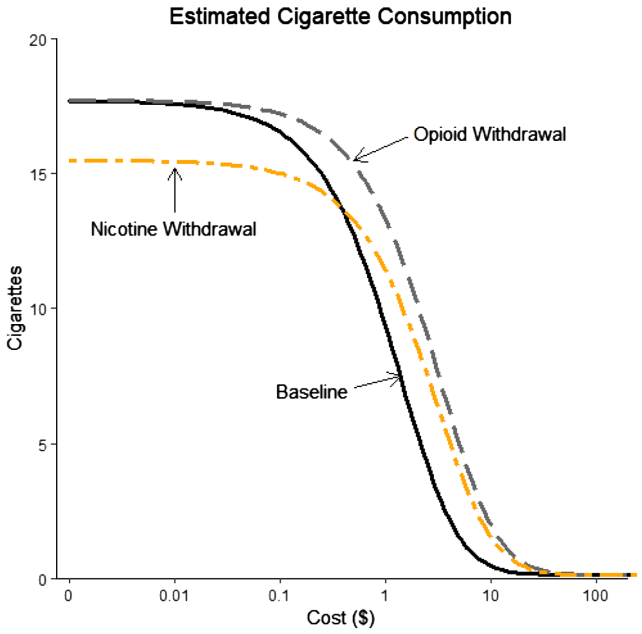
Estimated coefficient values for both Q_0 and α are shown in Figure 4. There were no significant differences between Q_0 values based on withdrawal condition for opioid consumption. For α, differences between baseline and cigarette withdrawal, $t(8,361) = 3.39$, $p = .002$, $d_z = 0.221$, and baseline and opioid withdrawal, $t(8,361) = 3.46$, $p = .002$, $d_z = 0.247$, were significant, indicating a lower sensitivity to price for opioids during both forms of withdrawal. A visual comparison between the estimated coefficients from the base model and covariate model can be found in Supplemental Materials Figure S12.

Correlation Between Drug Demand and Covariates

Individual predictions of Q_0 and α from each condition and drug from the base model were correlated with the FTND, DSM 5 OUD, sex, and monetary discounting. The full correlation matrix can be found in Table 3. Effects that were found to be significant in the regression models also showed small to moderate correlations in the same direction. Generally, there was a strong correlation within drug type for estimated Q_0 and α between withdrawal conditions ($r > .66$). That is, opioid Q_0 and α estimates were most related to other opioid Q_0 and α estimates from other withdrawal conditions. However, estimates were more correlated within a drug and while under hypothetical withdrawal. For example, opioid Q_0 and α under

Figure 1

Predicted Demand for Cigarettes Based on Condition



Note. *Y*-axis is the number of cigarettes consumed. *X*-axis is the cost per cigarette in dollars $\log_{10}$ scaled. Each curve represents the predicted consumption based on withdrawal condition. Note that values of 0 were converted to .001 to allow for plotting on the $\log_{10}$ scale. Baseline consumption (i.e., no withdrawal) is the solid black line. Consumption under opioid withdrawal is the dashed gray line. Consumption under nicotine withdrawal is the orange (light gray) dashed-dotted line. See the online article for the color version of this figure.

opioid withdrawal was more related to opioid Q_0 and α under cigarette withdrawal than baseline withdrawal. For monetary discounting, delay discounting for the larger magnitude was positively related to opioid Q_0 and negatively related α, while probability discounting for the larger magnitude followed the inverted pattern. That is, those with lower self-control based on delay discounting and higher risk-taking based on probability discounting were more likely to demonstrate higher Q_0 and lower α. Correlations within discounting type were strong ($r > .75$), but weaker between discounting type ($r = .24$–$.36$).

Mixed-Effects Modeling

Due to the relative novelty of the mixed-effects modeling approach for demand, derived Q_0 values from the base model for each participant were compared to their empirical consumption at $0 cost to assess the accuracy of the fitted parameters to known empirical data. A scatterplot comparing these can be found in Figure 5. The correlation between Q_0 and consumption at $0 cost was high ($r = .986$, $p < .001$), indicating that the individual curves derived from the mixed-effects approach corresponded well with observed individual demand data. Deviations between derived and observed zero consumption mostly occurred when a participant would put a lower consumption at $0 but still otherwise produced a typical demand curve for other values.

Discussion

As predicted, withdrawal for either drug increased defending of commodity consumption over higher prices (i.e., lower price sensitivity) for both cigarettes and opioids indicating a cross-drug effect of withdrawal on valuation of these drugs. Previous research by MacKillop et al. (2012) found that acute nicotine withdrawal (12-hr deprivation) increased demand for cigarettes, but to our knowledge, this is the first demonstration of changes in demand of one drug as a function of withdrawal to another drug. However, because price sensitivity was lower under both conditions for both drugs, this provides preliminary evidence that demand can be used as a potential way to further study cross-drug withdrawal effects of drugs. That α for opioids was lowest under the cigarette withdrawal condition when controlling for potentially relevant covariates demonstrates how withdrawal of one drug can worsen the abuse liability of another. This also provides some support to the previous opioid and nicotine relationships where increased use of one drug is used to decrease withdrawal symptoms of the other (e.g., Mannelli et al., 2013). While this was a crowdsourced study and situations

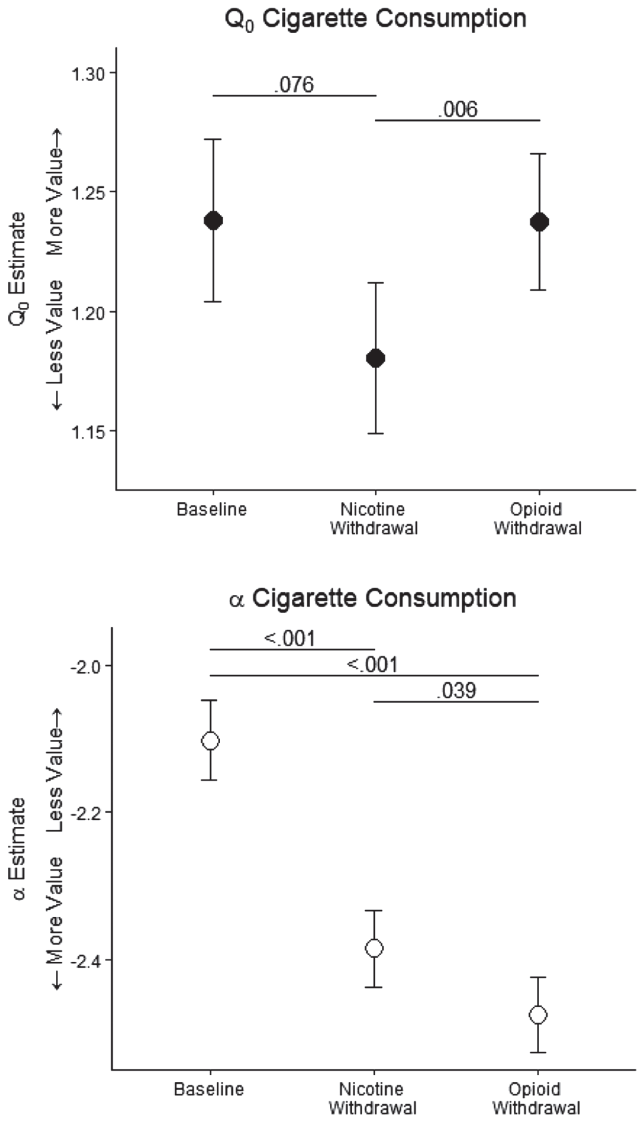
Table 2

Nonlinear Regression Estimates of Demand for Cigarette and Opioid Consumption

	Cigarette Demand					Opioid Demand				
Model term	Est.	*SE*	*df*	*t*	*p*	Est.	*SE*	*df*	*t*	*p*
Q_0 Intercept	1.205*	0.049	7,287	24.437	<.001	0.595*	0.049	8,355	12.212	<.001
Q_0 Opioid Withdrawal	0	0.023	7,287	−0.02	.984	0.018	0.025	8,355	0.747	.455
Q_0 Cigarette Withdrawal	−0.058*	0.026	7,287	−2.176	.03	0.041	0.024	8,355	1.699	.089
Q_0 Male	0.067	0.056	7,287	1.186	.236	0.2*	0.057	8,355	3.5	<.001
Q_0 FTND	0.123*	0.029	7,287	4.311	<.001	0.028	0.029	8,355	0.96	.337
Q_0 DSM 5 OUD	−0.045	0.029	7,287	−1.577	.115	0.078*	0.029	8,355	2.684	.007
α Intercept	−2.164*	0.081	7,287	−26.77	<.001	−2.439*	0.115	8,355	−21.15	<.001
α Opioid Withdrawal	−0.372*	0.04	7,287	−9.357	<.001	−0.247*	0.069	8,355	−3.586	<.001
α Cigarette Withdrawal	−0.282*	0.041	7,287	−6.967	<.001	−0.221*	0.063	8,355	−3.517	<.001
α Male	0.123	0.096	7,287	1.284	.199	0.013	0.128	8,355	0.102	.919
α FTND	−0.112*	0.048	7,287	−2.32	.02	−0.082	0.064	8,355	−1.271	.204
α DSM 5 OUD	−0.187*	0.049	7,287	−3.815	<.001	−0.207*	0.065	8,355	−3.189	.001

Figure 2

Nicotine Demand Parameters by Withdrawal Condition



Note. Estimated Q_0 (consumption when cigarettes are free; Top Panel) and α (sensitivity to change in price for cigarettes; Bottom Panel) parameters for cigarettes from the mixed-effects model that includes the Fagerström Test for Nicotine Dependence, DSM 5 criteria for opioid use disorder, and sex. Estimates are in $\log_{10}$ scale. Higher values of Q_0 are indicative of higher consumption, whereas lower values of α are indicative of less sensitivity to increased prices. Errors bars represent standard error of the estimate. Comparisons with $p < .1$ are indicated by the significance bars. Note that units are in $\log_{10}$.

were hypothetical, participants responded in ways that are amenable to this idea. Given that purchase tasks have been predictive of real treatment outcomes (González-Roz et al., 2020; Schwartz, Blank, et al., 2021; Secades-Villa et al., 2016), changes in α due to hypothetical cross-drug withdrawal indicates that those who co-use cigarettes and opioids may have worse treatment outcomes, as they would be more liable to increase drug consumption following cross-drug withdrawal, and continued use of the nontargeted drug appears to worsen treatment outcomes for the other (Mannelli et al., 2013; Parker et al., 2020).

Cross-Drug Withdrawal Interactions

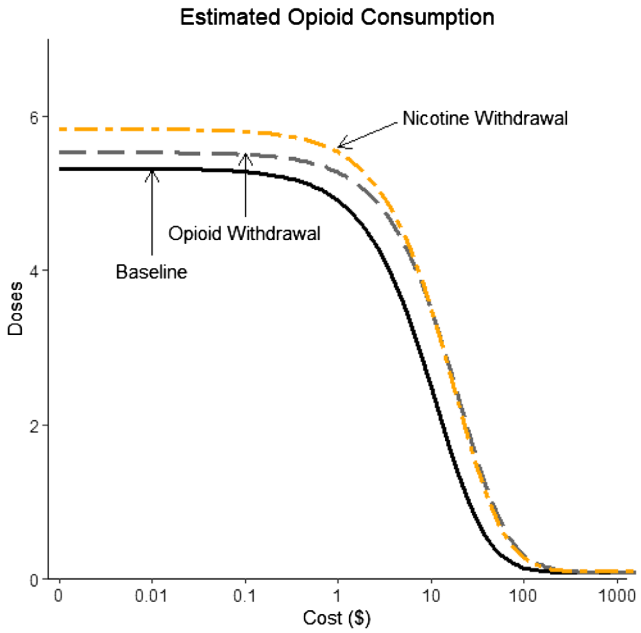
Withdrawal did not have cross-drug interactions with intensity of drug consumption (i.e., Q_0), indicating that quantity of drug consumed when consumption is not restricted by price is unaffected by withdrawal. This is against our original prediction of how cross-drug withdrawal would affect consumption. Lack of results with intensity of opioid consumption may be due to either there not being an effect of cross-drug withdrawal on this parameter, or could be due to our definition of opioid dose as the individual participants' usual dose. This could have led to heterogeneity among the dose quantity consumed and overall opioid intake among participants. Cigarette intensity decreased during the nicotine withdrawal condition, rather than increase as has been shown previously (MacKillop et al., 2012). There are two main reasons as to why this may be the case. In some instances, participants responded that they had imagined having quit cigarettes in the nicotine withdrawal condition (e.g., "Maybe even relieved that I have started the process of quitting"). This trend seems to be apparent in some of the individual data where participants engaged in zero consumption during the nicotine withdrawal relative to baseline. Because the phrasing of the nicotine withdrawal scenario was "For the following questions, imagine that you have not smoked a cigarette for some time and you are now in withdrawal from cigarettes," participants could have imagined themselves in a scenario where they were trying to quit cigarettes and believed they would not purchase or consume cigarettes as part of that quit attempt. This is a possibility as a timeframe of withdrawal was not specified. It is also worth noting that in a meta-analysis of laboratory manipulations of smoking, there was only a small correlation between cravings and consumption ($r = .15$; Gass et al., 2014). Another alternative is that the subjective experience of having a cigarette after an extended period of not smoking can be unpleasant (e.g., dizziness, nausea; Niaura et al., 2001) and participants imagined this effect during the withdrawal conditions. This could explain some of the decrease in intensity for cigarettes while in nicotine withdrawal while also resulting in a lower price sensitivity for cigarettes. That is, participants were may have been less likely to smoke a large number of cigarettes but continue to pay more to defend that number of cigarettes when under nicotine withdrawal. Alternatively, it is possible that some participants may have misunderstood the instructions which led to these counterintuitive outcomes (e.g., lower cigarette Q_0 in cigarette withdrawal conditions). However, given there was a comprehension check required prior to every demand condition, misunderstanding the instructions may have been unlikely.

Associations with Drug Demand

An interesting finding is the relationship between demand and monetary discounting measures. Delay discounting has been implicated as an important process in the development of substance use disorders as part of a model of reinforcer pathology (Bickel et al., 2014). In this model, low self-control and high demand ultimately lead to a pathological consumption of some commodity (i.e., drugs). In the present study, delay discounting at both magnitudes was significantly related to price sensitivity. As self-control decreased (i.e., higher k values), α for both cigarettes and opioids decreased.

Figure 3

Predicted Demand for Doses of Opioids Based on Condition



Note. *Y*-axis is the number of opioid doses consumed. *X*-axis is the cost per opioid dose in dollars $\log_{10}$ scaled. Each curve represents the predicted consumption based on withdrawal condition. Note that values of 0 were converted to .001 to allow for plotting on the $\log_{10}$ scale. Baseline consumption (i.e., no withdrawal) is the solid black line. Consumption under opioid withdrawal is the dashed gray line. Consumption under nicotine withdrawal is the dashed-dotted orange (light gray) line. See the online article for the color version of this figure.

Probability discounting was also related to α, but only at the $1,000 magnitude. In this case, higher values of *h* (i.e., preference for the smaller, certain option; less risky) were positively related to α. Therefore, those who were "less risky" were also less likely to defend consumption as prices increased for both drugs but only for the higher magnitude of probabilistic outcomes. To our knowledge, this is the first study that incorporated both delay and probability discounting and their relationship to demand for opioids.

Measures of use severity (i.e., FTND, DSM 5 OUD) were also related to demand metrics. This also replicates previous demand research for cigarettes (González-Roz et al., 2019) and opioids (e.g., Strickland et al., 2019). Further, there was specificity based on the measure and the drug consumed, as intensity was only significantly related to the respective severity of use measure for that drug. However, the DSM 5 OUD score was associated with change in α for cigarettes. Whether this relationship is consistent needs to be further examined, although it would be expected given the relationship between opioid and nicotine use. Interestingly, sex was only related to Q_0 for opioid consumption, where males were likely to have higher Q_0 than females. A main effect of sex and α was not identified as a significant factor in the model, nor was there a significant interaction based on withdrawal condition, despite previous research on different sex response to opioid withdrawal. Higher opioid Q_0 for males could be due to weight differences, or decreased effectiveness of opioids as analgesics when correcting for weight in males (Niesters et al., 2010). This could also be due to the hypothetical nature of the present study. However, understanding sex differences for cross-drug withdrawal of opioids and cigarettes warrants further exploration and identify those are higher risk of relapse.

Limitations

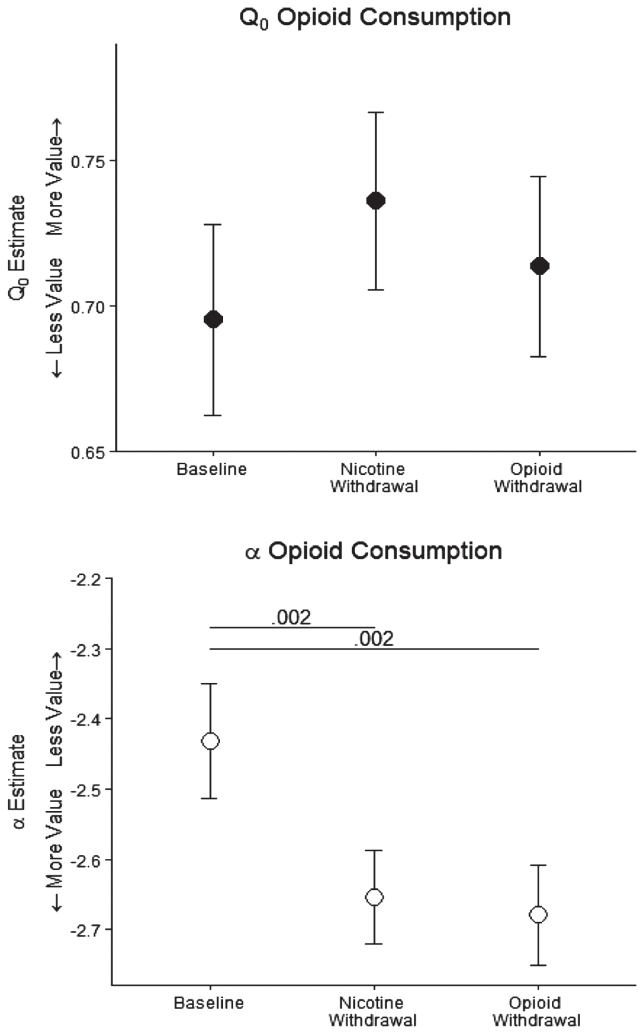
Limitations of the study include the inability to verify drug use in our crowdsourced participants, the hypothetical nature of withdrawal and purchasing conditions, and potential demand characteristics. While these are limitations, results of the present study showed similar effects of relevant covariates (e.g., FTND) on demand measures of studies that did not use crowdsourcing (e.g., Chase et al., 2013; Schwartz, Silberberg, et al., 2021). Additionally, there appears to be good correspondence between real and hypothetical demand tasks (e.g., Wilson et al., 2016), and purchase tasks are predictive of real treatment outcomes (González-Roz et al., 2020; Schwartz, Silberberg, et al., 2021; Secades-Villa et al., 2016; Yoon et al., 2020). It is possible that participants could have responded to experimenter expectations rather than the experimental manipulations (i.e., demand characteristics/good subject effect; Orne, 1962). As the manipulations were obvious, participants may have assumed that the "correct" way to respond under withdrawal conditions would be to increase consumption over baseline conditions. While there were significant effects on withdrawal conditions and α, responding to Q_0 did not follow as if participants were simply trying to produce "good" data. This is most notable in the Q_0 for cigarette consumption going in the opposite direction as predicted. This seems like the opposite of the expected direction of effect if responding was a result of demand characteristics. However, the good subject effect in studies of demand is an important consideration and more research needs to be done on it to determine how it may influence results. Although other studies examining other behavioral economic measures such as experimental manipulations of delay discounting found limited or no support for the good subject effect (Rung & Madden, 2018, 2019).

Future Directions and Best Practices

The use of crowdsourcing and hypothetical tasks allowed for an initial investigation of how withdrawal conditions affect consumption without requiring expensive and time-consuming procedures. Further research needs to clarify the relationship between cross-drug withdrawal and demand, as well as implications for treatment. For example, while cross-drug withdrawal decreased change in price sensitivity, how simultaneous withdrawal of both substances at once affects drug valuation should be examined. Because factors such as increased feelings of opioid withdrawal while smoking (Mannelli et al., 2013) and decreased quit likelihood of smoking for opioid users (Parker et al., 2020), targeting only a single drug during treatment may worsen outcomes compared to targeting both together. This is somewhat supported by the decreased sensitivity to price based on cross-drug withdrawal for both drugs assessed. Because price sensitivity has been useful in predicting treatment outcomes (González-Roz et al., 2020; Schwartz, Blank, et al., 2021; Secades-Villa et al., 2016), determining how cross-drug withdrawal affects demand may be an important target of investigation because of its predictive utility. Further research could also help to inform drug treatment practices

Figure 4

Opioid Demand Parameters by Withdrawal Condition



Note. Estimated Q_0 (consumption when opioids are free; Top Panel) and α (sensitivity to change in price for opioids; Bottom Panel) parameters for opioids from the mixed-effects model that includes the Fagerström Test for Nicotine Dependence, DSM 5 criteria for opioid use disorder, and sex. Estimates are in $\log_{10}$ scale. Higher values of Q_0 are indicative of higher consumption, whereas lower values of α are indicative of less sensitivity to increased prices. Errors bars represent standard error of the estimate. Comparisons with $p < .1$ are indicated by the significance bars. Note that units are in $\log_{10}$.

regarding concurrent smoking cessation during opioid treatment programs and behavioral processes that may be involved in nicotine and opioid co-use. Because smoking and opioid use appear to be important to target simultaneously, polydrug withdrawal (e.g., concurrent nicotine and opioid withdrawal) demand studies could help determine best practices when the goal is to decrease opioids or cigarette consumption. This can be accomplished through purchase tasks which would assess perceived consumption under polydrug withdrawal, or through real effort to obtain a drug during abstinence conditions.

Results of the present study provide useful considerations for the use of crowdsourced methodologies in substance use research. For example, even though some of the data seemed to be counterintuitive (e.g., Q_0 for cigarette consumption), there may have been valid reasons for this. The instructions for the withdrawal conditions did not specify why participants were in withdrawal, just that they were in withdrawal. This may have allowed some participants to imagine that withdrawal was a quit attempt and responded in such a manner. Specificity when priming for various scenarios should be considered as participants may behave in ways that are "correct" in the scenario that they imagine, but not necessarily in the way the researcher intended. Allowing for qualitative responses helps to verify correct interpretation of study instructions, but also provide clarity as to why some responding may differ than what is hypothesized. This is in line with the methodological considerations brought forward by Strickland and Stoops (2019) for using ways to improve or determine the validity of data collected during crowdsourced addiction research.

This also leads to important considerations concerning quality checks in crowdsourced data. While primary data exclusion was based on excessively high consumption, secondary analyses were also conducted based on quality of open-ended responses and systematic demand criteria. While the results of the primary analysis did not change following removal of the six suspect participants, excluding an entire participant's data for meeting any unsystematic demand criteria had an effect on the results. Notably, Q_0 for cigarettes still followed the same pattern of lower consumption during cigarette withdrawal from other conditions but was no longer significantly different. Similarly, Q_0 for opioid consumption was significantly higher in both withdrawal conditions. However, withdrawal conditions affected the ΔQ criteria (Stein et al., 2015) which identified individuals who may have been responding as not consuming a drug during withdrawal conditions as a function of a quit attempt (i.e., zero consumption across all prices). Excluding individuals based on standardized or presumed response patterns may not be a reasonable way to improve data quality, as some "unsystematic" data may be appropriate responding based on the context. This consideration is in line with the recommendation of Stein et al. (2015) regarding the importance of context-specific considerations for using the algorithm to remove "unsystematic" data paths. Removing participants that were unsystematic under any condition resulted in an analysis that had 35 fewer participants. Transparency in data exclusion, and sensitivity analyses comparing included/excluded data, could help improve the quality of crowdsourced studies in addictions when conducting exploratory research.

Conclusion

Due to the high rates of comorbid nicotine and opioid use, further research needs to be conducted to better understand how withdrawal from these drugs affects consumption of one another. In this study, crowdsourcing was a useful tool to identify how these two drugs may interact with each other when undergoing various states of withdrawal. Crowdsourcing also allowed for a larger sample than what would be normally possible and provided insight into an understudied interaction between two drugs with abuse potential. Further research should examine these relationships under experiential withdrawal conditions and the implications of these cross-drug withdrawal effects on treatment practices and outcomes.

Table 3

Correlation Matrix of Individual Demand Parameters From all Conditions Against Covariates of Interest

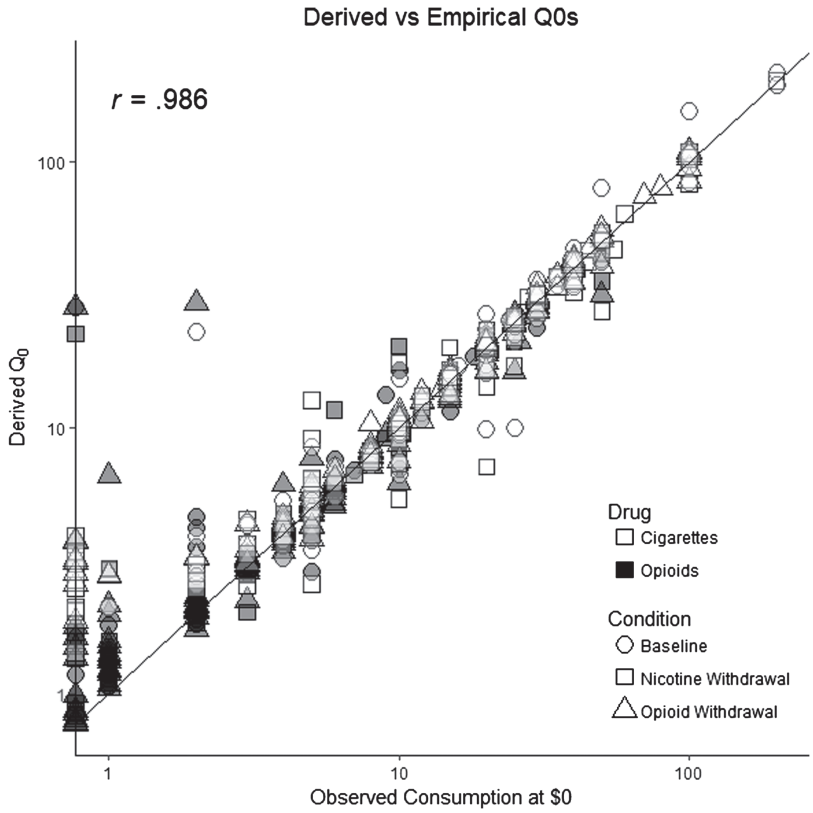
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. O BL Q_0		.73*	.75*	.31*	.22	.22	−.19	−.26*	−.21	−.19	−.16	−.13	.05	.18	−.15	−.16	.11	.24	.27*
2. O OW Q_0	.73*		.85*	.35*	.47*	.48*	−.17	−.33*	−.28*	−.16	−.14	−.09	0	.12	−.06	−.02	.12	.25	.27*
3. O CW Q_0	.75*	.85*		.35*	.42*	.39*	−.22	−.26	−.25	−.17	−.15	−.09	−.01	.11	−.06	−.05	.15	.22	.22
4. C BL Q_0	.31*	.35*	.35*		.73*	.66*	−.05	.03	.04	−.05	−.01	−.01	−.04	−.04	−.03	.07	.27*	.01	.04
5. C OW Q_0	.22*	.47*	.42*	.73*		.88*	.02	−.05	0	0	−.08	−.04	−.09	−.09	−.06	.04	.26*	−.01	.05
6. C CW Q_0	.22*	.48*	.39*	.66*	.88*		−.04	−.13	−.09	−.08	−.14	−.15	−.05	−.07	−.01	.01	.31*	.04	.08
7. O BL α	−.19*	−.17*	−.22*	−.05	.02	−.04		.59*	.66*	.52*	.43*	.45*	−.05	−.16	−.06	.11	−.14	−.2	−.04
8. O OW α	−.26*	−.33*	−.26*	.03	−.05	−.13	.59*		.91*	.6*	.61*	.62*	−.06	−.13	.05	.25	−.12	−.25	−.06
9. O CW α	−.21*	−.28*	−.25*	.04	0	−.09	.66*	.91*		.6*	.6*	.64*	−.11	−.16	−.01	.17	−.19	−.29*	−.02
10. C BL α	−.19*	−.16*	−.17*	−.05	0	−.08	.52*	.6*	.6*		.83*	.85*	−.14	−.17	.06	.18	−.23	−.28*	.06
11. C OW α	−.16*	−.14	−.15	−.01	−.08	−.14	.43*	.61*	.6*	.83*		.9*	−.21	−.2	.03	.18	−.27*	−.31*	.04
12. C CW α	−.13	−.09	−.09	−.01	−.04	−.15	.45*	.62*	.64*	.85*	.9*		−.17	−.18	0	.14	−.27*	−.32*	.09
13. *k* $100	.05	0	−.01	−.04	−.09	−.05	−.05	−.06	−.11	−.14	−.21*	−.17*		.75*	.29*	.24	.12	.07	−.11
14. *k* $1,000	.18*	.12	.11	−.04	−.09	−.07	−.16*	−.13	−.16*	−.17*	−.2*	−.18*	.75*		.36*	.28*	.09	.11	−.12
15. *h* $100	−.15*	−.06	−.06	−.03	−.06	−.01	−.06	.05	−.01	.06	.03	0	.29*	.36*		.8*	−.03	−.16	−.13
16. *h* $1,000	−.16*	−.02	−.05	.07	.04	.01	.11	.25*	.17*	.18*	.18*	.14	.24*	.28*	.8*		−.05	−.14	−.16
17. FTND	.11	.12	.15	.27*	.26*	.31*	−.14	−.12	−.19*	−.23*	−.27*	−.27*	.12	.09	−.03	−.05		.34*	−.03
18. OUD	.24*	.25*	.22*	.01	−.01	.04	−.2*	−.25*	−.29*	−.28*	−.31*	−.32*	.07	.11	−.16*	−.14	.34*		.11
19. Sex	.27*	.27*	.22*	.04	.05	.08	−.04	−.06	−.02	.06	.04	.09	−.11	−.12	−.13	−.16*	−.03	.11	

Note. Pearson correlation matrix from individual demand parameters, Q_0 and α, from each participant based on the base model (i.e., no covariates), monetary discounting, and other covariates. O = Opioid consumption. C = Cigarette consumption. BL = Baseline (i.e., no withdrawal). OW = Opioid withdrawal. CW = Cigarette withdrawal. Q_0 = Estimated consumption at $0 cost. α = Estimated sensitivity to change in price, lower values indicate lower sensitivity. *k* = Log monetary discounting for delayed outcomes, lower values indicate higher self-control. *h* = Log monetary discounting for probabilistic outcomes, lower values indicate higher riskiness. FTND = Fagerström test for nicotine dependence. OUD = DSM 5 opioid use disorder score. Sex = Coded as 0, female, and 1, male, resulting in a point-biserial correlation coefficient. Positive correlations for sex indicate males have higher scores, whereas negative correlations indicate that females have higher scores.

* Significant correlation at the .05 level, values above the diagonal have been adjusted for multiple comparisons.

Figure 5

Scatterplot of Estimated Q_0 Parameters for All Participants (y-axis) From the Base Model (i.e., no covariates) Compared to Their Observed Consumption at $0 (x-axis)



Note. Both axes are $\log_{10}$ scaled. Darkened points represent opioids while white points are cigarettes. Conditions are indicated by circles (baseline), squares (nicotine withdrawal), and triangles (opioid withdrawal). Diagonal line is a slope of one. Because the model was estimated in $\log_{10}$ space, Q_0 estimates were converted to raw consumption by the formula $Q_{0,\text{Raw}} = 10^{Q_0}$. Data points that fall on the *y*-axis line are observed consumptions of 0 at $0. The Pearson correlation is in the top left of the plot.

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