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Assessing the functions of prescription stimulant abuse among college students

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ASSESSING THE FUNCTIONS OF PRESCRIPTION STIMULANT ABUSE AMONG COLLEGE STUDENTS

by

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Abstract

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Non-medical prescription stimulant use (NMPSU), such as using medications like Ritalin, Adderall, and Concerta without a prescription or at a higher dosage than prescribed, is a rising trend in American adults. Use is most prevalent among college age adults (18-25 years old). Survey research among experienced users has identified several reasons college students are engaging in NMPSU, including enhancement of cognitive, athletic, and social performance, but less is known about how the relative reinforcing value differs based on the reasons of use. Behavioral economic drug purchase tasks have been used to capture reinforcer strength and motivation related to use of prescription drugs and other substances. For this study, we developed the Functional Purchase Task to measure demand for stimulant-like drug effects. A sample of 116 students experienced with NMPSU were recruited from two universities. Descriptive results indicated the highest endorsed reasons for use corresponded with higher demand across multiple metrics. Mixed model comparison analysis demonstrated that while demand for stimulant medications does differ based on reason for use, individual preference is a better predictor for demand. These initial results support the importance of accounting for function of use when assessing reinforcer strength, and encourage adoption of a functional approach to future studies using hypothetical purchase task measures.

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Chapter One: Introduction

Non-medical prescription stimulant use (NMPSU) has been an increasing public health concern, particularly among young people. NMPSU involves use for non-medical reasons and can be operationally defined as the use of stimulant medication without a prescription, in excess of what is recommended (Bavarian, Flay, Ketcham, & Smit, 2015), or by administration routes other than oral (nasal, intravenous, other; Burtner, Behling, Cassidy, & Butler, 2018). Frequently this involves medications typically prescribed to treat attention deficit/hyperactivity disorder (ADHD), such as amphetamine (Adderall and Vyvanse), dextroamphetamine (Dexedrine) or methylphenidate (Ritalin and Concerta). The 2017 Monitoring the Future survey reported that young adults levels of amphetamine use have gradually and steadily increased, over the past 20 years with levels of use among college students nearly doubling to 9% from 1996 to 2017 (Schulenberg Johnston, O'Malley, et al., 2017, p. 14). The 2017 National Survey on Drug Use and Health reported that 715,000 young adults (18 to 25 years old) abused stimulants in 2017 with 187,000 of them having a stimulant use disorder (SAMHSA, 2018). Proportionally, young adults use stimulants at a rate 4 times higher and suffer stimulant use disorders at rates 2.5 times higher than adults 26 and older, further documenting that young people are at highest risk of abusing these medications (Substance Abuse and Mental Health Services Administration, 2018).

Elevated use in this age group may be attributable to particularly high NMPSU among college students (Johnston, Bachman, & Schulenberg, 2011; Schepis, Teter, & McCabe, 2018). Research on the age of onset of NMPSU suggests that this behavior is primarily initiated after a student enters college (Arria et al., 2008; Bavarian, Flay,

Ketcham, & Smit, 2013). Although the true overall prevalence is unclear, a review of survey research conducted between 2000 and 2013 found variable rates of NMPSU across different universities (Bavarian et al., 2015), with as many as one third of the students reporting NMPSU at some schools (DeSantis, Webb, & Noar, 2010; Garnier-Dykstra, Caldeira, Vincent, O'Grady, & Arria, 2012). Longitudinal data from one university suggests this may be an increasing trend, as increases in past-year and lifetime NMPSU prevalence between 2003 and 2013 were observed (5.4% to 9.3% and 8.1% to 12.7%, respectively; McCabe, West, Teter, & Boyd, 2014). These findings are consistent with national data, which show an increasing trend in nonmedical amphetamine use among college students from 2008 through 2012 and annual prevalence of nonmedical Adderall use at about 10% for the past decade (Schulenberg et al., 2017). These trends are concerning given that prescription drug abuse is associated with elevated rates of binge drinking, tobacco, marijuana, other illicit drug use, and risky sexual behavior (Benotsch, Koester, Luckman, Martin, & Cejka, 2011; McCabe, Knight, Teter, & Wechsler, 2005).

Possible Reinforcing Functions of NMPSU Among College Students

The self-reported reasons why students engage in NMPSU include cognitive enhancement to improve academic achievement, improved alertness to stay awake or improve athletic performance, increased sociability and recreational high, and weight loss through appetite suppression (Arria et al., 2008; Arria & DuPont, 2010; Niloofar Bavarian et al., 2013; Brandt, Taverna, & Hallock, 2014; Jeffers, Benotsch, & Koester, 2013; McCabe et al., 2005; Teter, McCabe, LaGrange, Cranford, & Boyd, 2012; White, Becker-Blease, & Grace-Bishop, 2006). These findings suggest that there are likely many

different functions maintaining NMPSU for different users; however, there are no existing measures to assess these functions beyond self-reported reasons for use. Research in fields such as autism spectrum disorder and developmental disabilities empirically supports functional analyses of behavior showing that it can help better inform diagnosis and improve intervention outcomes (Beavers, Iwata, & Lerman, 2013; Iwata, Dorsey, Slifer, Bauman, & Richman, 1994). Therefore, research that allows us to better measure and understand the functions maintaining NMPSU among college students may help us better address it, as well.

Behavioral Economic Demand as a Measure of Drug Reinforcing Efficacy

The field of behavioral economics presents an approach to identifying the putative reinforcing effects of NMPSU. This approach integrates concepts and methods from operant psychology and micro-economics to explain decision-making processes of humans. Within this framework, demand (i.e. the amount of a commodity sought or consumed at a given price) is a fundamental construct in the quantification of the reinforcing efficacy of drugs (i.e., the degree to which a consequence strengthens a behavior; cf. Bickel, Marsch, & Carroll, 2000). Behavioral economic research suggests that differences in demand for a drug can provide a meaningful index of the abuse liability of that drug for individual users and groups.

In recent years, demand has been quantified using hypothetical purchase tasks (HPT) in which individuals are asked to indicate consumption values for a good (e.g., an alcoholic drink) across a range of escalating hypothetical prices. Using these consumption values, demand and expenditure curves can be plotted that yield several

demand indices that can be used to quantify the relative reinforcing efficacy for an individual. These demand indices include intensity of demand (the consumption at lowest price, usually zero); breakpoint (the price at which consumption first reaches zero); O_{max} (the maximum expenditure value); P_{max} (the price point corresponding to maximum expenditure); and elasticity (the relative change in consumption as response cost increases; Amlung, McCarty, Morris, Tsai, & McCarthy, 2015). These HPTs allow researchers to assess the abuse liability of a drug while circumventing the need for in-vivo human drug administration.

HPTs have been used to assess the reinforcing efficacy for a wide range of substances, including alcohol (Amlung et al., 2015; Gentile, Librizzi, & Martinetti, 2012; Murphy & MacKillop, 2006), marijuana (Collins, Vincent, Yu, Liu, & Epstein, 2014; Strickland, Lile, & Stoops, 2017; Yurasek, Dennhardt, & Murphy, 2015), cocaine (Bruner & Johnson, 2014), tobacco (Heckman et al., 2018; Liao et al., 2013; MacKillop et al., 2008) as well as nonmedical sedative, opioid, and stimulant medication use among non-prescriptive using college students (Pickover et al., 2015). Indices derived in this HPT paradigm demonstrate strong psychometric properties through good test–retest reliability (Murphy, MacKillop, Skidmore, & Pederson, 2009), correspondence with actual consumption choices in a laboratory setting (Amlung, Acker, Stojek, Murphy, & Mackillop, 2012), and prediction of treatment outcomes following brief drinking interventions (Murphy et al., 2015). Although these studies have established the validity of the demand analysis approach to quantifying reinforcing efficacy, they have not addressed whether reinforcer efficacy might differ depending upon the specified function of the drug (e.g., cognitive enhancement, athletic performance, sociability, etc.).

Use of HPT to Measure Drug Function

The use of demand analysis as a measure of reinforcer efficacy depending on drug function may have implications for assessment and intervention of NMPSU. For example, if demand for stimulants differs across specified drug function, and the function of drug use differs across individuals, then rank ordered preference of drug function would best predict measures of demand. This would suggest tailoring interventions to students depending on their reasons for use. Preferred drug function on an individual basis might also predict which students are more likely to develop substance use disorders. For example, students whose preferred drug function is to enhance academic performance may be less likely to develop other SUDs later in life compared to those whose preferred drug function is to feel elated. The purpose of this study is to develop a Functional Purchase Task (FPT) to assess the demand for prescription stimulants among experienced users depending upon different functions of NMPSU (based on the self-reported reasons for use identified from the research literature).

We have three research questions:

> **Research question 1**: Does demand differ by specified drug function? That is, if consumption data are aggregated for specific functions (i.e., better focus, increased athletic performance, etc.), do demand curves for specified functions separate and do demand indices differ between functions?
>
> **Research question 2**: Does demand differ depending upon ranked choice? That is, if individuals are asked to rank preferred reasons for use, and consumption data

are aggregated and plotted for the four ranked drug function of their choice, do these curves separate and predict demand indices?

Research question 3: Does specified drug function predict demand intensity beyond ranked choice? That is, is there sufficient individual differentiation in ranked order of the drug functions across individuals such that specified function will independently predict drug demand intensity?

Chapter Two: Method

Participants and Procedures

Undergraduate college students from two similarly sized public Eastern and Mid-western universities were screened for participation. To be included in the survey students needed to report being 18 years or older, a current student, and having engaged in NMPSU during their lifetime. Students were recruited using the SONA student research pool and were rewarded with course credit in one of their courses for participation. An additional subset of students were recruited over a campus wide email announcer and entered into a drawing for gift cards. The survey was administered anonymously via the Qualtrics website and course credit was awarded through the SONA website system. Students provided informed consent and all procedures and materials were approved by the institutional review board prior to beginning study enrollment at the respective institution.

Measures

Demographic and NMPSU questions. In addition to basic demographic information, students were asked questions adopted from McCabe, Boyd, and Teter's (2009) prescription drug survey to assess for current or lifetime NMPSU. NMPSU was described as prescription stimulant use without a prescription, taking stimulants at a higher dose than recommended, or taking stimulants through a non-oral route of administration (nasal, intravenous, other). Additionally, participants were asked if they had ever been diagnosed with ADHD, which stimulant medications they had taken

(Adderall, Ritalin, Concerta, Vyvanse, etc.), and how many times they had engaged in NMPSU in the past year.

Ranking preferred drug functions. Before completing the purchase tasks, participants were asked to rank the importance of each drug effect in a hierarchy from one to eight, with one indicating their most preferred reason for use (i.e., drug function) and their eighth choice being the least preferred reason for use. They were provided the following instructions:

> In the questionnaire that follows, we would like you to pretend to purchase and consume stimulant medications (Adderall, Ritalin, Concerta, etc.). Research has shown that the following are common reasons people take stimulants. Please arrange these effects by dragging and dropping them in the order of their importance to you. The top is the most and the bottom is the least important.

These eight common stimulant drug effects, generated from those typically reported reasons of NMPSU from previous research (McCabe, Boyd, & Teter, 2009) included: 1) Reduce your appetite; 2) Make you feel awake and boost energy/alertness; 3) Help you focus better and longer; 4) Improve your academic achievement; 5) Improve your athletic performance; 6) Help you get along with others more easily; 7) Give you an overall sense of feeling on top of the world; and 8) Counteract the effects of other drugs/alcohol.

Functional purchase task (FPT). All participants were directed to read the following instructions before continuing to the purchase tasks:

> The following questions ask you to pretend to purchase and consume stimulants, such as Ritalin, Adderall, Dexetrine, or Concerta. Pretend that you: have the same income/ savings that you have now, have no access to any drugs other than the pills offered at these prices, will consume all the pills that you purchase on that day, and cannot save or sell any pills. Everything you buy is for your own personal use within the day on which you purchase them. Please carefully read and respond to these questions honestly, as if you were actually in this situation.

These instructions were worded based on similar HPT studies (i.e. Murphy & MacKillop, 2006; Pickover, Messina, Correia, Garza, & Murphy, 2015). At the beginning of each purchase task, participants were informed that the stimulants came in pill form, were administered orally, and peak drug effects would occur between one and two hours in a total four-hour window. They repeated the purchase task four times and at the beginning of each they were instructed to pretend the pills had only one main effect. The effect specified on each trial was drawn from the eight functions (e.g. reduce appetite, improve academic achievement, etc.) listed above. For each participant the four functions specified were those they had ranked as their first, second, fifth, and eighth ranked reasons for use. The selection of these ranked choices was done to reduce response burden on participants while enabling the collection of consumption data across a range of ranked choices. The order in which the purchase tasks were presented was randomized to reduce order effects.

Parameters of interest. Consumption data from the purchase tasks were used to derive the demand indices for each specified drug function and for the first, second, fifth, and eighth ranked choices. Intensity of demand (how much someone will consume when

the substance is free); breakpoint (the price at which an individual is no longer willing to purchase the substance); O_{max} (the maximum amount of money spent on the substance); P_{max} (price at which maximum expenditure occurred); and elasticity (changes in consumption patterns as the price of the substance increases (Pickover et al., 2015) were derived. Essential value (*EV*) was also included as a theoretically constant composite measure of reinforcing strength that may be important for comparing drug functions (Hursh & Silberberg, 2008). *EV* is a standardized metric inversely related to demand elasticity and calculated independent of unit size.

Due to the expected large number of zero consumption values for lower ranked drug functions, the exponentiated demand curve equation was used to estimate the elasticity of demand. This solution was first proposed by Yu and colleagues (2014) and developed further by Koffarnus and colleagues (2015) to better handle zero data than the other available methods: $Q = Q_0 * 10^{k(e^{-\alpha Q_0 C} - 1)}$. In the equation: Q = consumption at a given price; Q_0 = maximum consumption; k = a constant that denotes the range of consumption values across individuals; C = cost (price) and α = the derived elasticity parameter reflecting the rate of decline in consumption across escalating costs (Koffarnus et al., 2015). A k constant was determined based on the range of consumption values to provide best fit to the mean demand curves. Elasticity of demand was plotted using GraphPad Prism 7 for Macintosh OSX (GraphPad Prism 7 Software, San Diego, CA; www.graphpad.com). P_{Max}, O_{Max}, and *EV* were derived from Q_0, k, and α using the "Kaplan and Reed Essential Value, P_{Max}, and O_{Max} Automated Calculator" (Kaplan & Reed, 2014).

Data handling procedures. A common problem when using HPTs is the collection of consumption data that do not systematically reflect expected elastic change by price. This may be due to task directions being unclear or not followed (i.e. not responding with the assumption of a 24 hour period to purchase and consume drugs), inattention to the task (i.e. not responding in accordance to price listed), or errors in response entry (e.g., typing 11 pills instead of 1 pill). Two general assumptions to determine if data are systematic include (1) a reduction in consumption from lowest price to highest price and (2) a consistent change in direction of consumption across price increments (Stein, Koffarnus, Snider, Quisenberry, & Bickel, 2015). Stein and colleagues (2015) developed three criteria to identify nonsystematic data; trend, bounce, and reversal. In the case of trend patterns, where consumption data reflect negligible reductions, no change, or increases in consumption as price increases, a relative change score can be used to identify and remove individuals who exhibit such patterns. However, following these criteria would result in removing data when a participant indicated they would not purchase the substance at any price (i.e., no change or trend). Removing all such participants could ignore valid responding because "purchasing" zero pills at any price would mean there is no demand for the drug given the specified function. In other words, it would indicate that the drug does not serve that function. Therefore, a relative change score of $\Delta Q = 0$ was calculated using the equation provided by Stein et al. (2015) to identify participants who exhibited nonsystematic trend increases in consumption, and not those who provide inelastic or zero consumption data. Additionally, participants may exhibit bounce patterns (variable increases and decreases in consumption despite increasing price) or more specific reversal patterns (resumed purchasing at a higher price

after ceasing at a lower price). In these cases, participant data was only retained for calculation of demand intensity (Q_0) but excluded from calculation of other demand indices to preserve fidelity of elastic measures of demand and breakpoint.

Based on initial piloting of the FPT, an additional criterion of nonsystematic data used in this study was the exclusion of "extreme values." This was operationally defined as consumption values that exceed what would be reasonable for an experienced stimulant user completing the purchase task, and would compromise the fidelity of demand analyses. An example of this could be a participant, who endorsed having experience with NMPSU, indicating they would purchase more than 1000 pills to consume in a 24-hour period. Similar to previous studies using indices of demand derived from HPT consumption data, a decision criterion of consumption of 20 or more pills was treated as outlier data and removed from analysis.

Data Analysis Plan

The first research question of whether demand differs by specified drug function was addressed through demand curve graphics of the FPT consumption data for each specified drug function. Demand indices derived from the consumption values collected from the FPT (i.e. demand intensity, O_{Max}, P_{Max}, breakpoint, elasticity, and essential value) were examined to determine how demand differed based on specified function. Additionally, descriptive visual analyses using median dot plots for average rank of stimulant drug effects across individuals were generated to illustrate the average rank order of functions across the entire sample. Interquartile ranges and raw data jittering were included for the median dot plots to reflect variability of rank order within the

sample (Ward, 2007). Analysis for the second research question whether demand differs depending upon ranked choice also included a demand curve graphic illustrating FPT consumption data as a function of ranked choice of drug function preference (first, second, fifth, and eighth choice) with a table of corresponding demand indices.

Nested model comparison analyses were used to address research question three of whether specified drug function predicts demand intensity beyond ranked choice. Because the assumption of independence is violated, as each participant contributed four scores of demand intensity for their first, second, fifth, and eighth preferred drug function, generalized linear model comparisons were utilized. A Poisson distribution was used to fit the dependent variable. This approach also had the advantage being able to handle data that may have been highly zero inflated, violating assumptions of normality. Two generalized linear models were constructed: the full model contained participant ID as a fixed effect, with ranked choice and drug function as independent variables to predict demand intensity, compared to the reduced model of participant ID as a fixed effect and ranked choice only. Multi-level comparisons were used to assess for changes in variance retained when drug function was added to the model. Decrease in Akaike's information criteria (AIC) was used to determine which model best fit the data. For the AIC metric, smaller values indicate a better model fit. A likelihood ratio test was used to determine if adding drug function as a predictor variable contributes to the fit of the model beyond the reduced model only including ranked choice and participant ID. A p-value of $<.05$ indicated a significant contribution and supported retaining specific drug function in the model.

Chapter Three: Results

Participants were predominantly white, heterosexual, undergraduates, between 18-23 years of age. Most had a GPA of 3.0 or higher and were employed at least part-time. (see Table 1). The eastern university had significantly more male, employed respondents with GPAs less than 3.4. Data on NMPSU are reported in Table 2. Lifetime NMPSU was endorsed by 17.5% (N=116) students out of 664 screened. Of those endorsing NMPSU, 57.8% (n=67) reported past year use and 13% (n=15) reported using more than five times during the past year. Over one third (38.8%, n=45) reported using at a higher dose than recommended, and 23.3% (n=27) reported a non-oral route of administration. Almost all of the students reported oral administration (n=115, 99.1%), but 20.7% (n=24) endorsed nasal and 2.6% (n=3) endorsed intravenous or other administration. More than half of the sample reported never having an ADHD diagnosis (55%, n=52) or current prescription (57.8%, n=67). Thus, the majority of students who engaged in NMPSU did so infrequently at appropriate dosages and administration routes, but without an ADHD diagnosis or current prescription.

Table 1
Demographic characteristics of student sample

	Total Sample		*Eastern University*		*Midwestern University*		*p-value*
	N = 116	*%*	*n =76*	*%*	*n = 40*	*%*	
Biological Sex							**<.001**
Male	56	48.3	46	68.8	10	25.0	
Female	60	51.7	30	31.2	30	72.5	
Race/Ethnicity							.52
White	86	74.1	53	66.6	33	82.5	
Black/African American	6	5.2	4	6.3	2	5.0	
Latino/Hispanic	7	6.1	6	10.4	1	2.5	
Asian	7	6.1	6	12.5	1	2.5	
Other	10	8.5	7	4.2	3	7.5	
Sexual Orientation							.16
Heterosexual	82	70.7	59	83.3	23	57.5	
Bisexual	14	12.1	7	6.3	7	17.5	
Gay or Lesbian	6	5.1	3	2.1	3	7.5	
Other	14	12.1	7	8.3	7	17.5	
Level of Education							.33
Freshman/1st year	29	25	21	35.4	8	20.0	
Sophomore/2nd year	33	28.4	20	35.4	13	32.5	
Junior/ 3rd year	23	19.8	18	20.8	5	12.5	
Senior/ 4th year	18	15.5	9	6.3	9	22.5	
Other	13	11.2	8	2.1	5	12.5	
Age							.13
18-20	72	62.1	52	85.4	20	50.0	
21-23	26	22.4	15	12.5	11	27.5	
23+	18	15.5	9	2.1	9	22.5	
Cumulative GPA							**.02**
<2.9	25	21.6	18	22.9	7	17.5	
3.0-3.4	30	25.9	22	31.3	8	20.0	
3.5-3.9	42	36.2	20	20.8	22	55.0	
4.0+	5	4.3	3	4.2	2	5.0	
Do not know	14	12.1	13	20.8	1	2.5	
Employment Status							**<.001**
Work 1-20 hours/week	39	33.6	24	25.0	15	37.5	
Work 21+ hours/week	32	27.6	14	16.6	18	45	
Not employed	45	38.8	38	58.4	7	17.5	

Table 2
Sample characteristics of non-medical use of prescription stimulants

	Total Sample		*Eastern University*		*Midwestern University*		*p-value*
	N=116	*%*	*N=76*	*%*	*N=40*	*%*	
Past Year NMSPU							.57
0	49	42.3	32	37.5	17	42.5	
1-2	37	31.9	22	29.2	15	37.5	
3-5	15	12.9	12	16.7	3	7.5	
5<	15	12.9	10	16.6	5	12.5	
Higher Dose than Recommended							.83
Yes	45	38.8	30	33.3	15	37.5	
No	71	61.2	46	66.7	25	62.5	
Route of Administration							.65
Oral	115	99.1	76	65.5	39	33.6	
Nasal	24	20.1	16	13.8	8	6.9	
Intravenous	2	1.7	0		2	1.7	
Other	1	0.8	0		1	0.8	
Lifetime ADHD/ADD Diagnosis							.98
Yes	52	44.8	34	39.6	18	45.0	
No	64	55.2	42	60.4	22	55.0	
Current Stimulant Medication Rx							.21
Yes	49	42.2	32	37.5	17	42.5	
No	57	49.1	35	47.9	22	55.0	
No, but one in past	10	8.6	9	14.6	1	2.5	
Type of Stimulant Medication Used							
Adderall	92	79.3	57	75.0	35	87.5	
Ritalin	34	29.3	23	30.2	11	27.5	
Vyvanse	40	34.5	32	42.1	8	20.0	
Concerta	27	23.3	17	22.3	10	25.0	
Other	32	27.6	23	30.2	9	22.5	

The overall sample rankings of stimulant drug functions are included in Figure 1. The median dot plots suggest the cognitive enhancement functions (improve academic achievement, help focus, and boost energy and alertness) were ranked highest by most students, while other functions were ranked lower. However, the raw data jittering illustrates the presence of students who ranked the other drug functions higher.

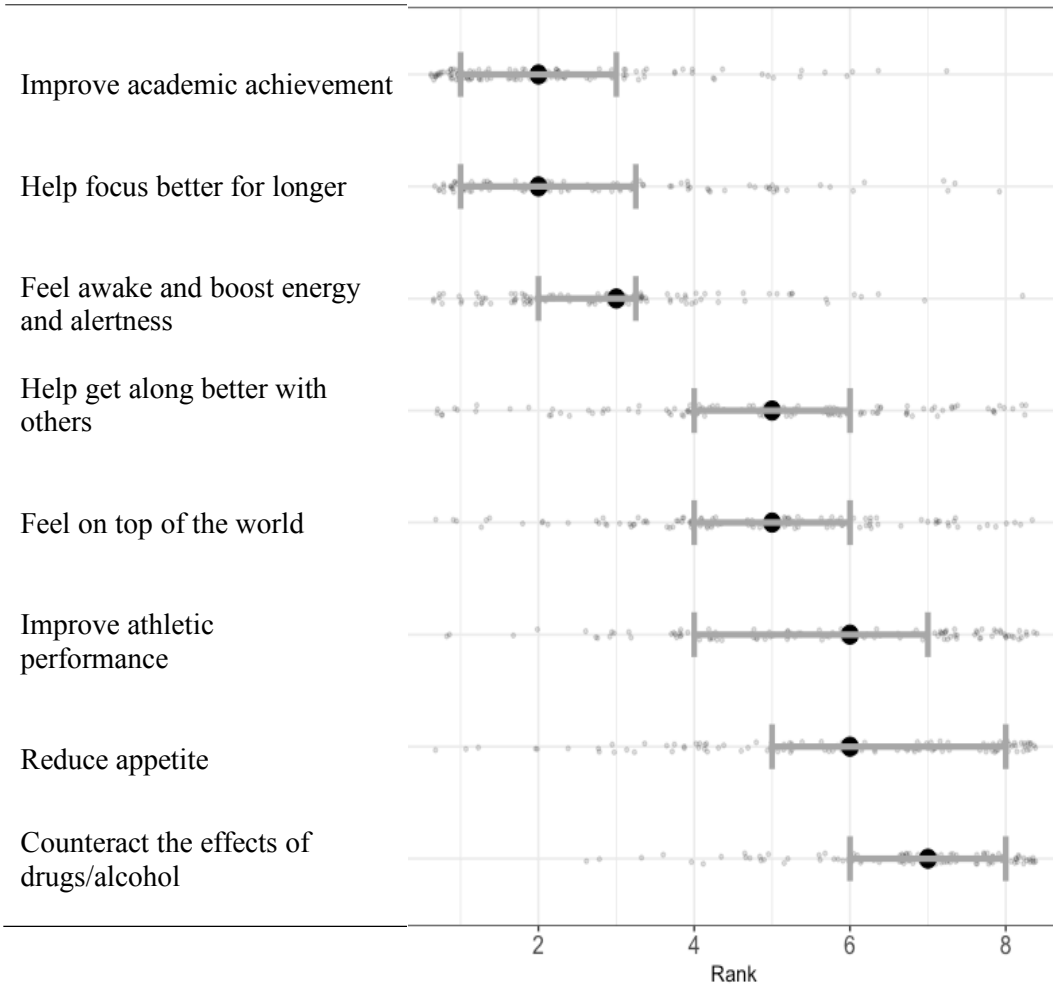

Figure 1. Median dot plots of student ranking across stimulant functions with interquartile range and raw data jittering.

Demand indices for each preferred choice and specified drug function are presented in Table 3. Ranked preferred choice and specified drug function are arranged according to most to least demand (Q_0). Seven participants exceeded the "extreme value" criterion and were removed due to Q_0 values greater than 15 pills. Seven additional participants exhibited nonsystematic trend, bounce, or reversal patterns (Stein et al., 2015), and were removed from calculation of the remaining demand indices. As a result, the mean value for the five demand indices (with the exception of Q_0) for each of the stimulant functions and preference ranks presented in Table 3 are based on the data from the remaining 102 participants.

For research question one (does demand differ by specified drug function?), demand curve plots were constructed using participant consumption data for each specified drug function in Figure 2. These data are represented in aggregate to illustrate separation between functions, and individually below the main graph because functions also overlapped, especially at higher price points. For each drug function, consumption patterns followed assumptions of demand (i.e. as price increased, consumption decreased). Model fit was excellent across each function (R^2>.94). The demand curves shown in Figure 2 correspond with the ranked order of stimulant functions in Figure 1 and with Q_0 and O_{max} in Table 3, consistent with the expected findings for research question one.

Table 3

Mean values for demand metrics across ranked preferences and drug functions

	Q_0*(n=109)	*BP*	P_{Max}	O_{Max}	**α**	*EV*
First Choice	2.98	7.32	10.64	9.57	0.015	0.416
Second Choice	2.67	6.71	10.22	8.25	0.018	0.359
Fifth Choice	1.49	4.58	9.93	4.53	0.028	0.191
Eighth Choice	0.47	1.30	3.98	0.57	0.338	0.025
Improve academic achievement	2.93	7.78	11.97	10.56	0.019	0.475
Help focus better for longer	2.85	4.99	9.56	8.21	0.021	0.363
Feel awake and boost energy and alertness	2.32	7.20	6.74	5.13	0.013	0.179
Help get along better with others	1.91	2.94	7.18	4.38	0.019	0.165
Feel on top of the world	1.64	1.12	8.32	4.81	0.004	0.101
Improve athletic performance	1.38	6.60	9.56	4.38	0.088	0.202
Reduce appetite	0.75	1.35	8.29	1.99	0.038	0.073
Counteract the effects of drugs/alcohol	0.72	5.85	5.16	1.16	0.086	0.046

Note: Outlier data were removed before calculation of Q_0(n= 109) and nonsystematic values were also removed from the remining indices (n=102)

Q_0: Demand intensity (consumption at $0 (free))

BP: Breakpoint (price when consumption first reaches zero)

P_{max}: Price corresponding to maximum expenditure)

O_{max}: Maximum expenditure value)

α: Alpha (elasticity parameter; relative change in consumption in response to change in commodity price)

EV: Essential Value (standardized composite of reinforcer value

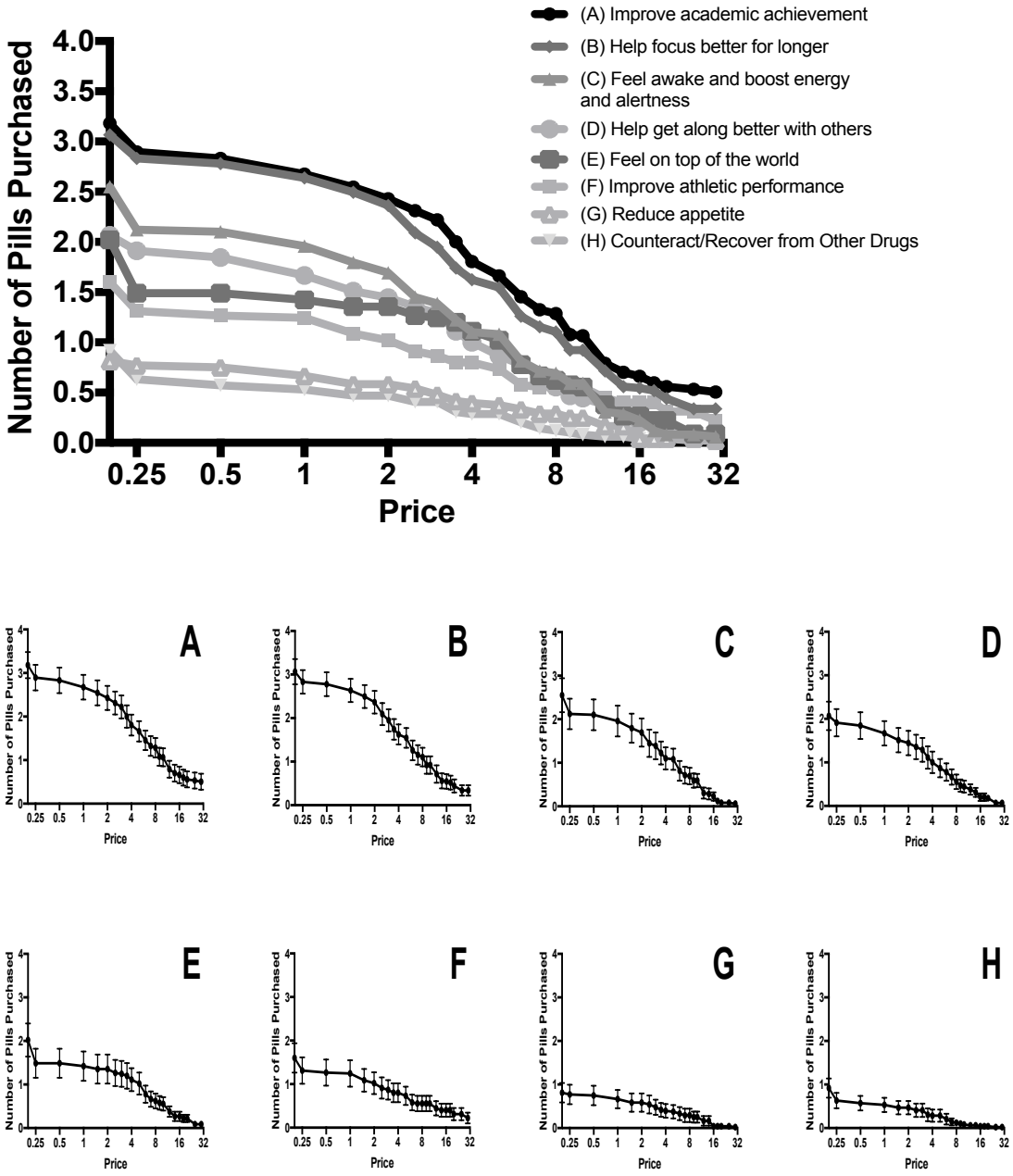

Figure 2. Hypothetical mean stimulant demand as a function of the number of pills bought and consumed at increasing prices across all stimulant drug functions.

Note: Aggregate demand curves are plotted for each function on the top and ordered according to most to least demand intensity, Q_0. Individual separated plots for each function are on the bottom. Error bars represent ±1 standard error of the mean.

For research question two (does demand differ by ranked choice?), demand curve plots were also constructed from participants' first, second, fifth, and eighth ranked choice of stimulant functions (see Figure 3). Across all four curves, consumption decreased as a function of increasing price, as expected, and participant performance exhibited higher demand associated with higher preference. Model fit was excellent across each plotted curve (R^2>.98). Again, the results in Figure 3 are consistent with the ranked order for drug functions in Figure 1 and the aforementioned demand indices in Table 3.

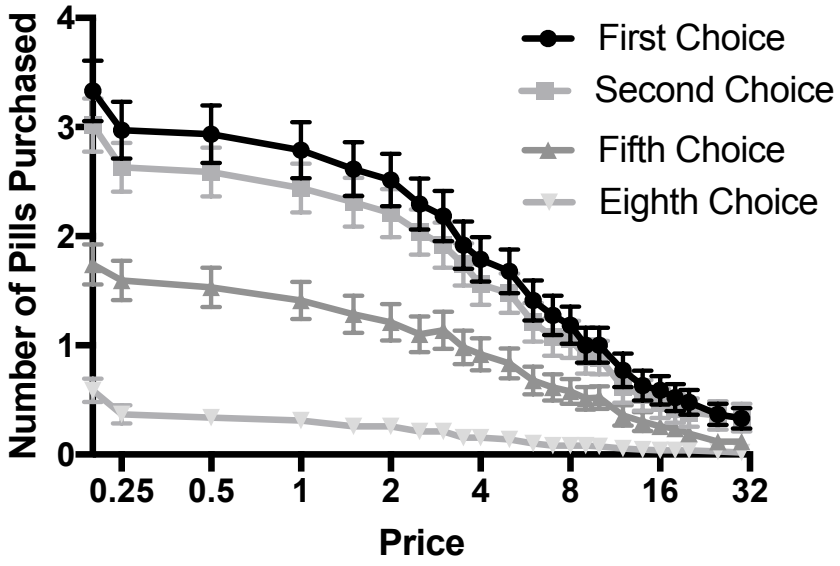

Figure 3. Hypothetical mean stimulant demand as a function of the number of pills bought and consumed at increasing prices across students' preferred rankings (n=102). Error bars represent ±1 standard error of the mean.

Research question three sought to answer whether specified drug function would predict demand intensity beyond ranked choice. Model 1 added participant ranked choice as the reduced model nested within Model 2 (the full model) which included ranked choice and drug function. Model comparison analysis used the AIC (model 1= 1307.2; model 2=1313.1). This small change in AIC between the full and reduced model indicates that the addition of drug function likely does not strongly predict demand intensity beyond ranked choice. A likelihood ratio test confirms this suspicion, as it indicates that the addition of drug function does not significantly aid in the fit of the model, χ-squared = 8.16, p = 0.319. The only significant result overserved once drug function was added was reduced appetite predicted lower demand intensity than the other seven drug functions. These results suggest adding specific drug function to the model does not contribute enough for predicting demand intensity to justify inclusion in the model and does not predict demand intensity beyond ranked choice.

Chapter Four: Discussion

These results suggest that while ranked choice and drug function appear to have implications in predicting demand for stimulants, there is likely considerable collinearity, at least within this college student population. For the first and second research questions regarding demand by drug function and preferred drug function, expected outcomes were supported by the results. The drug functions associated with the highest demand intensity were those expected from previous survey research suggesting college students are using stimulants to boost cognitive and academic performance. Also, students' more preferred drug functions were related to higher demand intensity, breakpoint, *Omax*, *Pmax,* and essential value, and to lower elasticity. This suggests that the self-reported reasons for use by individuals predict demand for stimulants such that those functions ranked higher have higher demand. Finally, while demand appears to differ according to function, ranked preference is the stronger predictor. Unranked drug function does not have enough unique contribution to improve the fit of the model. This is consistent with a behavior analytic perspective, in that examining how reinforcer value differs according to function at the individual level can be important when considering interventions even if functions on average are ranked similarly across individuals. Future research can examine how a larger sample size and different demand indices (elasticity, breakpoint, essential value, etc.) replicate or change this model fit.

There are several limitations to the current study, the first being generalizability of results to all college students. While consistent with similar studies using hypothetical purchase task paradigms, this study had a relatively small sample collected from two similar sized universities in two different regions of the United States. There were also

minor differences between samples that may have influenced the results. Although gender has not be found to produce differences in demand for stimulants in previous research (Pickover et al., 2015), stimulant abuse generally is proportionally more prominent among male than among female college students (Schulenberg et al., 2017) and substance use correlates with lower GPA (Musgrave-Marquart, Bromley, & Dalley, 1997). The university samples also differed significantly on employment, which might be thought to be related to income and a possible influence during purchasing tasks, which has been demonstrated to be sensitive to income in addition to price (Roddy, Steinmiller, & Greenwald, 2011). However, the samples did not differ in terms of financial status, likely because college students often receive financial support from families. More research is needed studying the effects of gender, GPA, and available income on demand and drug function. For example, do higher achieving students exhibit higher demand for stimulants when the underlying function is to increase cognitive performance?

Another aspect of the current study is the novel use of a functional purchase task to assess demand characteristics across drug functions. While this presents new opportunities in the rapidly expanding research occurring in the broader field of behavioral economics, this new functional purchase task has not been validated through independent replication. For example, future confirmatory factor analyses need to be done to assess collinearity between ranked preference and drug function. Based on these initial results, it is probable the overlap between the top three drug functions suggest a more umbrella "cognitive enhancement" function driving demand. It is also possible functions other than those included in the FPT will emerge as more qualitative and survey research is conducted on NMPSU among college students. Another related issue

regarding the use of the FPT is that it is not yet clear whether the measure is ecologically representative of college student NMPSU purchasing behavior. For example, this current study used a similar price range as Pickover et al. (2015) but it is possible this is not representative enough for this student population. While the purpose of the HPT paradigm is not to assess how students purchase drugs, there are important considerations to determine if the purchase task paradigm is ecologically valid. For example, do students generally purchase stimulants with the intention of consuming them in a single 24-hour period, or do they save and use them over a longer period of time? Is there a stable enough economic market to use monetary measures of reinforcer value, as considerable research on diversion reveals as many as a third of total stimulant medications are obtained from friends and family (Schultz, Silvestri, & Correia, 2017; Vrecko, 2015), suggesting prices and purchasing behavior may vary widely. Again, the purpose of the HPT paradigm is not to recreate a model drug buying economy, but interesting work is being done with other non-drug reinforcers, changing the time, price, or other parameters to better understand how these variables could produce changes in demand indices (Kaplan et al., 2017), and future studies could investigate how these manipulations might help in the refinement of a more ecologically valid FPT for NMPSU.

Despite these limitations, the Functional Purchase Task could have practical implications even if it does not reflect actual purchasing practices. It is possible that results from FPTs could be used to predict an individual's periods of higher drug use (e.g., around finals) or as a functional analysis to guide treatment. Research examining these possibilities is warranted.

In conclusion, this study provides support for continued use of behavioral economic approaches to understanding NMPSU and contributes meaningful data on the reinforcing demand for these drugs through analyzing patterns exhibited by college student users. Our results indicate that NMPSU is sensitive to response cost contingencies of monetary price increases, and demand for these drugs differs based on function. As previously discussed, further research is needed to evaluate the validity, reliability, and generalizability of using the Functional Purchase Task to assess the reinforcing efficacy of NMPSU. However, this initial study is an important step forward in both the study of NMPSU and the use of the functional purchase task paradigm. Additionally, while stimulant use may have similar functions for college students as a whole, the individual, ideographic reasons for use are what best predict demand. This represents a change from the majority of research on NMPSU, which is usually conceptualized as a nomothetic phenomenon assuming college students all use stimulants for the cognitive enhancement effects. There are implications for how NMPSU may be assessed and treated from this more idiographic perspective. Drug use treatment does not typically utilize a functional analysis, however the success of this approach in the treatment of Autism Spectrum Disorder and developmental disability (Beavers et al., 2013) suggests measures assessing drug function may lead to more individually personalized and contextually sensitive treatment. It is the hope that this initial research will advance interest in the assessment of functional differences on young adult prescription stimulant use, and of other socially important behavior.

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