Research Article

Current and Projected Cannabis Demand Predict Future Consumption in Young Adults Who Use Cannabis

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ABSTRACT

Objective: Cannabis demand, as measured by the Marijuana Purchase Task (MPT), holds associations with concurrent cannabis consumption and associated risks (e.g., cannabis use disorder [CUD]). As few studies have examined prospective associations between cannabis demand and future cannabis use, the current study examined this association in young adults who use cannabis. In addition, the present study explored the novel construct of projected future cannabis demand and its associations with future cannabis use. **Method:** Participants first completed a current Time1 (T1) MPT, projected future Time2 (T2) MPT (i.e., "three months from now"), and measures of past-month cannabis use frequency and CUD symptoms during an initial session. They returned three months later (T2) to complete a current T2 MPT and measures of cannabis use and CUD symptoms. **Results:** Measures across the three MPTs (observed T1, projected future T2, and observed T2) indicate relatively stability of demand across time and accuracy in projecting future demand. Prospective associations between T1 demand measures and cannabis use were observed, with both observed T1 and projected future T2 demand measures associated with T2 cannabis use frequency. **Conclusions:** Results of the current study highlight the potential of current and projected future cannabis demand measures to better understand the trajectory of cannabis use in this high-risk population.

Key words: = cannabis; demand; behavioral economics; marijuana purchase task; young adult

Cannabis is the most commonly used illicit drug in the United States, with 22.0% of Americans reporting cannabis use in the past year (SAMSHA, 2023), and is highest among young adults aged 18 to 25 (38.2%). The high prevalence of cannabis use among young adults is associated with a myriad of negative cannabis-related outcomes (Figueiredo et al., 2020; Grant et al., 2012; Patel & Amlung, 2019). Cannabis Use Disorder (CUD) in the past year is highest among young adults (16.5%; SAMSHA, 2023), representing a significant clinical and public health concern.

Cannabis misuse has been linked to the willingness to spend a considerable amount of time, effort, or money to obtain and use cannabis, suggesting a high reinforcing value (Bickel et al., 1998). Thus, behavioral economic theory views

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heavy cannabis use as an overvaluation of cannabis relative to non-cannabis reinforcers (Bickel et al., 2014). We can utilize behavioral economic methods, typically involving measurement of amount of output (i.e., cost) in order to gain access to a drug, to measure its relative reinforcing value (Rachlin, 1997). The Marijuana Purchase Task (MPT; Aston et al., 2015; Collins et al., 2014) is a hypothetical commodity purchase task that examines relative reinforcing value, or demand, by asking participants to imagine a typical day when they would use marijuana, and report how much marijuana they would purchase for consumption at a variety of prices.

Cannabis Demand and Use

The MPT is a widely-used, valid assessment of the relative reinforcing value of cannabis (for review, see Aston & Meshesha, 2020), and measures from the MPT are correlated with real world measures of cannabis consumption (Aston et al., 2015; 2016a; González-Roz et al., 2023; Strickland et al., 2017). Specifically, high demand for cannabis is an independent risk factor for problematic use, and individuals with any cannabis dependence symptoms show significantly higher demand intensity and more inelastic demand (i.e., relative insensitivity to price increases) compared to those with less problematic use. The MPT has demonstrated that higher demand for cannabis among young adults is correlated with higher cannabis consumption, poor executive functioning, and driving while impaired by cannabis (Coelho et al., 2023; Patel & Amlung, 2019). Taken together, the existing literature suggests that cannabis demand as measured by the MPT can offer insight into concurrent cannabis use.

Findings from existing literature also suggest that demand metrics may predict future substance use. For example, current alcohol demand is associated with drinking quantity and heavy drinking days in the future, even after accounting for risky alcohol use (Strickland et al., 2019). In addition, alcohol demand measures among young men predict drink quantity, heavy drinking, and alcohol-related consequences 4 years later, even after accounting for the same measures at baseline (Gaume et al., 2022). Aston and Merrill (2023) demonstrated that alcohol demand intensity predicted drinking quantity at the next drinking event. Thus, alcohol demand may exhibit predictive validity for subsequent consumption beyond that of other concurrent alcohol use measures.

Some recent evidence suggests similar associations with cannabis use. Aston et al. (2023) examined the prospective relationship between cannabis demand and future cannabis use frequency at 6-months in a sample of military veterans. They found that higher baseline demand intensity, P_{max}, and breakpoint were associated with more frequent future cannabis use, indicating that cannabis demand measures may provide insight into future cannabis use.

The Current Study

Existing research establishes the relationship between cannabis demand and concurrent cannabis use frequency (Aston et al., 2016a; Strickland et al., 2017). Furthermore, alcohol demand is associated with future alcohol use (Aston & Merrill, 2023; Gaume et al., 2022; Strickland et al., 2019). However, the predictive relationship between current cannabis demand and future cannabis use in a sample of young adults is unknown. Thus, one aim of the current study is to extend the findings on alcohol (Aston & Merrill, 2023; Gaume et al., 2022; Strickland et al., 2019) to cannabis and extend findings on demand and concurrent (Aston et al., 2016a; Strickland et al., 2017) and future (Aston et al., 2023) cannabis use frequency. We expect that young adults' current cannabis demand will predict future cannabis use frequency.

In addition to standard demand measures, research indicates that projected future demand might also provide good insight into future consumption. For example, Aston and Merrill (2023) found associations between alcohol demand intensity projected for the next expected drinking event (i.e., later that same day) and subsequent alcohol consumption. Additionally, recent evidence shows that college students project significant increases in demand for 3 months in the future, and these projections are associated with future drinking (Kurnellas et al., 2025). Thus, a second aim of this project is to examine the novel construct of projected future cannabis demand. A modified MPT that asks participants to make purchasing decisions for a

future timepoint will allow for exploration of how young adults project their future cannabis demand and whether their projections are accurate. Considering this construct will also allow for evaluation of the relationship between projected future cannabis demand and future cannabis use, we expect that projected demand will predict future cannabis use frequency. To address these aims, we collected measures of concurrent cannabis demand, consumption, and projected future demand in an initial session, with measures of concurrent cannabis demand and consumption collected again 3 months later.

METHODS

Participants

One hundred and sixteen (N = 116) young adults were recruited using flyers posted in the community, on a university campus, and on local websites (e.g., Craigslist) in a state where cannabis use is legal only for medical use (i.e., recreational use is not legal). Participants were eligible to participate if they were between 18 and 29 years of age and reported using cannabis at least once in the past month. See Figure 1 for a full breakdown of participant exclusions. One (1) participant was ineligible to participate at recruitment due to not having used cannabis in the past month. Twenty (20) participants met at least one criteria for nonsystematic purchase task data (i.e., trend, bounce, reversals from zero; Stein et al., 2015) on at least one purchase task, leaving 95 participants with systematic purchase task data. Eighteen (18) participants who completed session 1 did not return to complete session 2. A final sample of 77 participants were included in all analyses (see Table 1 for demographic variables of the final sample), noting that 55 participants is the minimum sample size to obtain adequate statistical power (0.80 using G*Power, with α = .05, two-tailed) for the predicted medium effect size in a regression analysis with five predictor variables (Faul et al., 2007). Overall study design, effect size estimates, and sample size considerations were informed by Kurnellas et al. (2025). All procedures were approved by the university Institutional Review Board

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Figure 1. *Participant Exclusions*

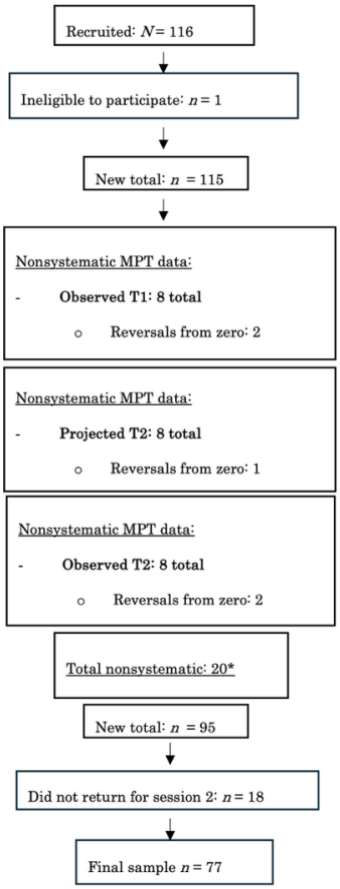


Table 1. *Participant Demographics*

Final sample: *n* = 77	
Variable	*% (n)*
Age in Years	*M* = 20.58 (*SD* = 2.4)
Gender	
Woman	48% (*n* = 37)
Man	52% (*n* = 40)
College Student	
Yes	95% (*n* = 73)
Freshman	18% (*n* = 14)
Sophomore	22% (*n* = 17)
Junior	19.5% (*n* = 15)
Senior	23% (*n* = 18)
Graduate School	9% (*n* = 7)
No	5% (*n* = 4)
Race/Ethnicity	
Asian	14% (*n* = 11)
Black or African American	8% (*n* = 6)
Indian	1% (*n* = 1)
White	69% (*n* = 53)
Other	4% (*n* = 3)
Multiracial	4% (*n* = 3)
Hispanic	
Yes	26% (*n* = 20)
No	73% (*n* = 56)
Yearly Income	
Less than $10,000	77% (*n* = 59)
$10,000 to $29,999	19% (*n* = 15)
$30,000 to $49,999	1% (*n* = 1)
Employment Status	
Full-time student / no job	43% (*n* = 33)
Employed full-time	5% (*n* = 4)
Employed part-time	16% (*n* = 12)
Full-time student / part-time job	29% (*n* = 22)
Self-employed or employment seeking	6% (*n* = 5)
Housing Situation	
Alone	9% (*n* = 7)
With roommates/partner/parents	91% (*n* = 70)
Cannabis Route of Administration (ROA)	
Smoke Only	53% (*n* = 41)
Vape Only	4% (*n* = 3)
Eat Only	3% (*n* = 2)
Concentrate Only	3% (*n* = 2)
Multiple ROAs	37% (*n* = 29)

Measures

Marijuana Purchase Task (MPT; Aston et al., 2015). The computerized MPT asked participants to read a vignette, placing several constraints on their consumption (e.g., cannot use marijuana kept from before, cannot stockpile) and report how much marijuana they would purchase for consumption. Cannabis hits were quantified as 0.09g of participants' typical cannabis grade and potency (i.e., 10 hits = 1 joint or 0.9 g or 1/32nd of an ounce), consistent with previous literature (Aston et al., 2015). Participants entered the number of hits they would smoke if one hit would cost them the

following prices : $0 (free), $.25 increments to $2, $.50 increment to $7, and $1 increments to $10 (22 total prices).

During the first session (T1), participants completed a standard MPT for a typical day during the past month (observed T1 demand) and a projected future MPT for a typical day three months in the future (projected T2 demand). The projected T2 demand MPT asked participants to report purchasing decisions for 3 months in the future (see both vignettes in Appendix A). Participants returned three months later to complete a second standard MPT (observed T2 demand).

Timeline Follow-Back (TLFB). We used the TLFB methodology to assess cannabis consumption frequency during the past month (Robinson et al., 2014). Participants were given paper handouts with TLFB calendars, marked with relevant holidays and events to best assist participants with accurately reporting how many days they consumed cannabis in the past 30 days.

DSM-V Cannabis Use Disorder (CUD) Symptoms. Participants indicated if they have experienced any of the 11 symptoms of CUD (yes/no) in the past 12 months, including withdrawal and craving, based on criteria in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5; American Psychiatric Association, 2013).

Procedure. This study was conducted across two in-person sessions, occurring three months apart. Participants received a total of $30 in the form of a prepaid debit card if they participated in both sessions (~ 75 min each). Immediately after the first session they received $10, and after attending the second session, the card was reloaded with an additional $20. If the first questionnaire in session 1 indicated ineligibility, the participant received a prorated compensation of $5 and was discontinued.

Consent and Baseline – Time 1 (T1). In the first session, participants first provided written informed consent. Following a demographic survey and a CUD questionnaire, participants completed a short interview to complete the TLFB. Subsequently, participants completed a standard MPT and projected future MPT on a personal computer in a private room. The experimenter read instructions prior to administering each assessment and was available to answer questions.

Time 2 (T2). The second session occurred ~3 months after the first session (mean days between sessions = 95 [*SD* = 8.29], median = 93) in the same setting. The procedure was similar to T1, except that participants did not complete the demographic survey nor the projected future MPT. We note that CUD symptoms were collected at this session, but as the assessment asks about past-year use (substantially overlapping with the T1 assessment), this second assessment is not included in any regression analyses.

Data Analysis

Data were scored and analyzed using IBM SPSS Statistics (version 29) and R programming language (R Core Team, 2023).

Cannabis use. Means and standard deviations were calculated for CUD symptoms and past-month cannabis use frequency from the TLFB at T1 and T2. Bivariate Pearson correlations were performed on CUD symptoms, past-month cannabis use frequency, and demand indices at each timepoint. All tests conducted were planned a-priori and theoretically informed, and thus no correction for potential inflation of type 1 error was conducted.

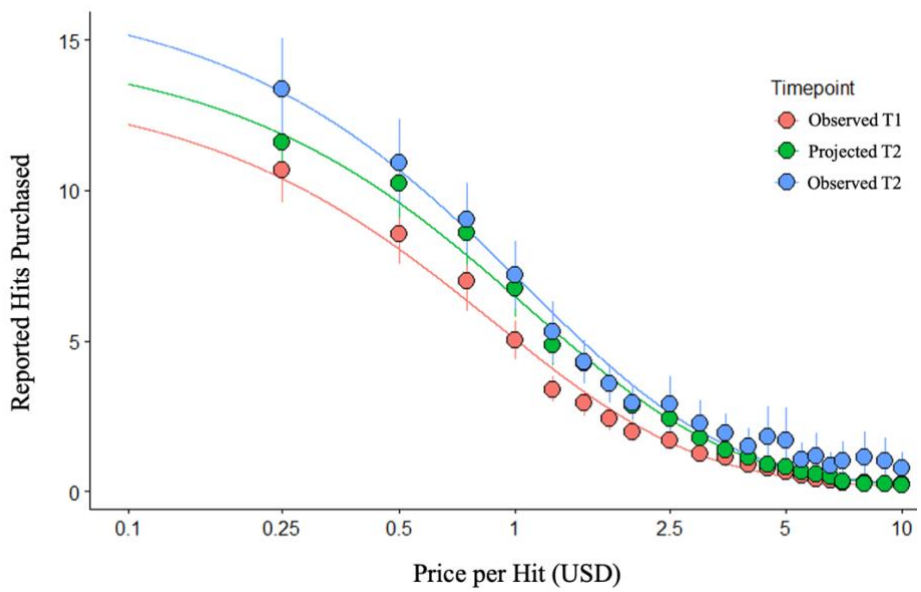
Demand. Responses on each MPT were screened for violations of trend, bounce, and reversals from zero and removed if at least one criterion was failed (Stein et al., 2015; see Figure 1). We conducted outlier analyses by identifying values ± 3.29 *SD*s at each price on the raw MPT data and replaced outliers with the greatest non-outlier value (Tabachnick et al., 2013),using the "beezdemand" R package (Kaplan et al., 2018).

The following individual-level observed demand indices were calculated: intensity (consumption when the commodity is available at no cost), P_{max} (the unit price at which maximum expenditure occurs), O_{max} (the expenditure associated with P_{max}) , and breakpoint (the lowest unit price at which consumption is zero). Elasticity of demand (indexing responsiveness of consumption to price increases, or price sensitivity) was empirically derived using the exponentiated demand equation (Equation 1; Koffarnus et al., 2015) at the group-level:

$$Q=Q_0 * 10^{k(e^{-\alpha Q_0 C}-1)}, \qquad (1)$$

where Q represents quantity consumed at a given price, Q_0 represents derived intensity (i.e., consumption as price approaches zero), k represents a constant across individuals that denotes the range of the dependent variable (hits), α represents the rate of change of elasticity, and C represents cost. Raising part of the equation to the power of 10 allows the untransformed consumption values including zero values to be fit. We used a consistent k value of 2.158429 (i.e., the mean of the three default k values) when model-fitting all purchase task data (see Figure 2 for group-level demand curves). Each demand measure was positively skewed and underwent log-10 transformations to achieve normality. Tests of normality, linearity, homoscedasticity, and absence of multicollinearity were performed to ensure that assumptions of linear regressions were met (Flatt & Jacobs, 2019; Mishra et al., 2019).

Figure 2. *Group-Level Demand Curves from Observed T1, Projected T2, and Observed T2 Data*



Note. n = 77. Note logged price axis.

Current Demand and Future Use

To examine if current cannabis demand predicts future cannabis use, we performed a series of linear regressions on observed T1 demand indices and future cannabis use. For each observed T1 demand predictor (i.e., intensity, O_{max}, P_{max}, breakpoint, and elasticity), separate linear regressions were performed to determine if current demand predicts future cannabis use frequency, as measured by the TLFB at T2. T1 CUD symptoms and T1 cannabis use frequency were added to the regression models one at a time to examine the partial effects of observed T1 demand indices.

Projected Demand

To examine projected change in demand (i.e., how participants think their demand will change in 3 months), projected change was calculated by subtracting observed T1 demand from projected T2 demand (see Table 2). Bivariate Pearson correlations were conducted on projected T2 and observed T1 demand. Paired-samples t-tests were performed on projected T2 and observed T1 demand to examine if participants project changes in demand.

To examine observed change in demand (i.e., how participants' demand actually changed in 3 months), observed change was calculated by subtracting observed T1 demand from observed T2 demand (see Table 2). Bivariate Pearson correlations were conducted on observed T1 and observed T2 demand to examine the relative stability of demand. Paired-samples t-tests were performed on observed T1 and observed T2

demand to examine if demand changes across timepoints.

To determine accuracy in projections, we performed delta calculations by subtracting observed T2 from projected T2 demand (see Table 3). Bivariate Pearson correlations were performed on the projected *change* and observed *change*, representing *relative* accuracy of projections. Paired-samples *t*-tests were performed on projected T2 and observed T2 demand to examine accuracy.

Projected Demand and Future Use

To examine if projected future demand predicts future cannabis use, we performed a series of regressions on projected T2 demand indices and future cannabis use. For each projected T2 demand predictor (i.e., intensity, O_{max}, P_{max}, breakpoint, and elasticity), separate linear regression models were estimated to determine if projected demand predicts the outcome of T2 cannabis use frequency. T1 CUD symptoms and T1 cannabis use frequency were added to the regression models one at a time to examine the partial effects of projected T2 demand indices.

Additional study measures and procedures not relevant to this study are reported elsewhere (Foxx et al., 2023).

RESULTS

Data Quality

To test the assumption of normality, predicted probability (P-P) plots of the residuals were examined and all plots demonstrated a normal distribution for each variable included in analyses. Scatterplots of residuals demonstrated patterns of homoscedasticity. The variance inflation factors (VIF) all fell below 5.00, indicating an absence of multicollinearity (Kutner et al., 2004). Thus, the data met all assumptions of linear regressions. The exponentiated model (Koffarnus et al., 2015) provided an excellent fit across purchase tasks (observed T1 R^2 mean = .900 [range .730 to .993], projected T2 R^2 mean = .883 [range .614 to .990], observed T2 R^2 mean = .912 [range .740 to .996]).

Table 2 provides descriptive statistics of all demand, projected change, observed change, and accuracy measures. Table 3 provides results on bivariate correlations between demand and cannabis use measures. Each projected T2 measure was correlated with its respective observed T1 and observed T2 measure; the novel projected demand task demonstrated adequate construct validity given its close associations with valid and reliable standard measures at two timepoints (Aston et al., 2015; Bush et al., 2023). Additionally, the exponentiated demand model yielded an R^2 mean of .883 for the projected task, demonstrating goodness of fit for these novel measures (Koffarnus et al., 2015).

Table 2. *Descriptive Statistics of Non-Transformed Observed T1, Projected T2, and Observed T2 Demand Indices; Descriptive Statistics and T-Test Results of Log-Transformed Projected Change, Observed Change, and Accuracy of Projections*

Demand Index	Observed T1 *M* (*SD*)	Projected T2 *M* (*SD*)	Observed T2 *M* (*SD*)
Intensity	11.25 (7.63)	12.64 (9.78)	14.14 (12.77)
O_{max}	6.81 (4.73)	8.89 (6.90)	9.23 (11.00)
P_{max}	2.20 (2.28)	2.05 (2.14)	2.01 (1.85)
BP_1	3.05 (2.78)	3.19 (2.81)	3.19 (2.76)
Elasticity (α)	.029 (.024)	.025 (.024)	.030 (.040)
	† Projected Change Δ (ProjT2-ObsT1)	† Observed Change Δ (ObsT2-ObsT1)	† Accuracy Δ (ProjT2-ObsT2)
Intensity	+.025 (.124)	+.052 (.238)	-.027 (.241)
O_{max}	+.075 (.176)**	+.048 (.297)	+.027 (.296)
P_{max}	-.012 (.175)	-.005 (.229)	-.007 (.229)
BP_1	+.015 (.121)	+.018 (.237)	-.003 (.229)
Elasticity (α)	-.001 (.005)*	+.001 (.013)	-.002 (.013)

Note. † Indices were log-transformed. *$p < .05$, ** $p < .01$. $n = 77$.

Table 3. *Bivariate Pearson Correlations of Demand and Cannabis Use Measures at Each Timepoint*

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Obs. T1 Intensity	-	.357**	-.236*	-.099	-.511**	.908**	.356**	-.265*	-.139	-.451**	.659**	.256*	-.302	-.122	-.237*	.321**	.182	.334**	.193
2. Obs. T1 O_{max}		-	.574**	.640**	-.860**	.319**	.808**	.490**	.560**	-.753**	.315**	.517**	.230**	.307**	-.470**	.035	.285*	.052	.292*
3. Obs. T1 P_{max}			-	.888**	-.441**	-.224	.435**	.722**	.770**	-.374**	-.138	.202	.499**	.439**	-.247*	-.078	.125	-.190	.169
4. Obs. T1 BP_1				-	-.557**	-.059	.545**	.733**	.887**	-.488**	.036	.352**	.554**	.565**	-.373**	-.045	.203	-.073	.205
5. Obs. T1 Elasticity					-	-.483**	-.741**	-.333**	-.489**	.868**	-.424**	-.511**	-.266*	-.369**	.557**	-.128	-.308**	-.187	-.303**
6. Proj. T2 Intensity						-	.488**	-.240*	-.032	-.538**	.677**	.327**	-.231*	-.037	-.264*	.247*	.195	.318**	.187
7. Proj. T2 O_{max}							-	.514**	.648**	-.858**	.394**	.567**	.248*	.374**	-.507**	-.051	.240*	.010	.216
8. Proj. T2 P_{max}								-	.847**	-.392**	-.177	.209	.481**	.411**	-.237*	.273*	.014	.336*	.002
9. Proj. T2 BP_1									-	-.567**	.004	.373**	.570**	.601**	-.370**	-.145	.122	-.148	.116
10. Proj. T2 Elasticity										-	-.425**	-.537**	-.289*	-.390**	.576**	.004	-.221*	-.072	-.222*
11. Obs. T2 Intensity											-	.621**	-.076	.172	-.491**	.207	.340**	.409**	.256**
12. Obs. T2 O_{max}												-	.471**	.641**	-.731**	-.033	.410**	.188	.293**
13. Obs. T2 P_{max}													-	.871**	-.435**	-.193	.148	-.107	.057
14. Obs. T2 BP_1														-	-.564**	-.085	.205	-.003	.133
15. Obs. T2 Elasticity															-	.091	-.165	-.112	-.101
16. T1 TLFB																-	.417**	.696**	.396**
17. T1 CUD																	-	.499**	.793**
18. T2 TLFB																		-	.426**
19. T2 CUD																			-

Note. Highlighted cells represent associations between Obs T1 and corresponding Proj T2 and Obs T2 demand measures. Boxed cells represent associations between Proj T2 and corresponding Obs T2 demand measures Demand indices were log-transformed. *$p < .05$ **$p < .01$. $n = 77$.

Current Demand and Future Cannabis Use

Our first aim was to examine if current cannabis demand is associated with future cannabis use frequency. Table 4 provides findings related to linear regression models of observed T1 demand predicting T2 cannabis use frequency (i.e., TLFB). Findings from the five unadjusted models demonstrated that observed T1 intensity was a statistically significant positive predictor of cannabis use frequency at T2 ($p = .003$). When T1 CUD symptoms were added as a covariate to the five adjusted models, observed T1 demand intensity was still a statistically significant positive predictor of cannabis use frequency at T2 ($p = .012$), and observed T1 P_{max} was a statistically significant negative predictor of cannabis use frequency at T2 ($p = .010$). When cannabis use frequency at T1 was added as a covariate to the five independent adjusted models, observed T1 demand intensity and P_{max} were no longer statistically significant predictors of future cannabis use frequency.

Table 4. *Linear Regressions of Observed T1 Demand Predicting Future Cannabis Use Frequency at T2*

Observed T1 Demand	Std. ß	Unstandardized B	*p*	R^2
Outcome: Timeline Follow-Back at T2				
Unadjusted Models				
Intensity	.334	12.948	.003**	.112
O_{max}	.052	2.068	.656	.003
P_{max}	-.190	-8.075	.097	.036
BP_1	-.073	-2.896	.530	.005
Elasticity (α)	-.187	-189.918	.103	.035
Adjusted for Timeline Follow-Back at T1				
Intensity	.123	4.767	.162	.489
O_{max}	.027	1.091	.746	.485
P_{max}	-.137	-5.815	.100	.503
BP_1	-.042	-1.659	.620	.486
Elasticity (α)	-.100	-101.293	.235	.494

Adjusted for Cannabis Use Disorder Symptoms at T1				
Intensity	.252	9.751	.012*	.310
O_{max}	-.099	-3.960	.348	.258
P_{max}	-.257	-10.902	.010*	.314
BP_1	-.181	-7.230	.076	.280
Elasticity (α)	-.037	-37.189	.730	.250

Note. Demand indices were log-transformed. All predictor variables were entered into separate models. *$p < .05$, **$p < .01$. $n = 77$

Existing research suggests that demand measures may fall into two factors holding distinct associations with aspects of substance use, with a latent two factor structure underlying demand indices (Aston et al., 2017; Bidwell et al., 2012; MacKillop et al., 2009). The latent factors are said to characterize Persistence (i.e., price insensitivity; elasticity, P_{max}, O_{max}, breakpoint) and Amplitude (i.e., volumetric consumption; O_{max} [at times] and intensity). Given our contrasting results, we conducted exploratory analyses on the associations between the latent factors of current demand and future cannabis use. Based on factor analyses by Aston et al. 2017, Persistence was calculated as the mean of the standardized observed T1 O_{max}, P_{max}, breakpoint, and elasticity scores. Prior to this calculation, elasticity values were reversed (i.e., 1/α) so that greater values reflect greater persistence (Bidwell et al., 2012). Amplitude was calculated as the mean of the standardized observed T1 intensity scores (Aston et al., 2017). Results of linear regressions indicate that Amplitude was a statistically significant positive predictor of T2 cannabis use frequency, even after accounting for baseline CUD symptoms (Standardized β = .282, R^2 = .328, p = 004). However, Persistence was *not* a statistically significant predictor of T2 cannabis use frequency (Standardized β = -.196, R^2 = .285, p = .056).

Projected Demand

Our second aim was to explore the novel construct of projected future cannabis demand. We examined if young adults project changes in their future demand for cannabis relative to current demand. Significant, positive bivariate correlations between observed T1 and projected T2 demand (see light gray cells in Table 2) suggest relative stability of projected future demand compared to observed T1 demand (r ranged from +.722 to +.908; all $p < .001$). Results of paired-samples t-tests on projected T2 and observed T1 demand measures indicate there were no significant differences in intensity, $t(76) = 1.791$, $p = .077$; P_{max}, $t(76) = -.602$, $p = .549$; or breakpoint, $t(76) = 1.045$, $p = .299$. However, projected T2 O_{max} was significantly higher compared to observed T1 O_{max}, $t(76) = 3.747$, $p < .001$, and projected T2 elasticity was significantly lower compared to observed T1 elasticity, $t(76) = -2.450$, $p = .017$.

We examined if demand in young adults changes across timepoints. Significant, positive bivariate correlations between observed T1 and observed T2 demand (see dark gray cells in Table 2) suggest relative stability in demand across timepoints (r ranged from +.499 to +.659; all $p < .001$). Results of paired-samples t-tests on observed T1 and observed T2 demand indices indicate that young adults did not display significant changes in intensity, $t(76) = 1.925$, $p = .058$; O_{max}, $t(76) = 1.413$, $p = .162$; P_{max}, $t(76) = -.206$, $p = .837$; breakpoint, $t(76) = .648$, $p = .519$; or elasticity, $t(76) = .374$, $p = .709$.

We examined if young adults are accurate in their projections of future cannabis demand. Bivariate correlations between projected T2 and observed T2 demand (see boxed cells in Table 2) revealed that projected T2 demand indices were statistically significantly, positively correlated with each of their respective observed T2 demand indices (r ranged from +.481 to +.677; all $p < .001$). Bivariate correlations between projected *change* and observed change in demand reveal that projected change in intensity ($r = +.230$, $p = .044$), O_{max} ($r = +.300$, $p = .008$), P_{max} ($r = +.382$, $p < .001$), breakpoint ($r = +.323$, $p = .004$), and elasticity ($r = +.240$, $p = .035$) are statistically significantly, positively correlated with each of their respective observed change variables, suggesting relative accuracy in projections. Results of paired-samples

t-tests on projected T2 and observed T2 demand indices indicate no statistically significant difference for intensity, $t(76) = -.979$, $p = .331$; O_{max}, $t(76) = .087$, $p = .422$; P_{max}, $t(76) = -.254$, $p = .800$; breakpoint, $t(76) = -.116$, $p = .908$; or elasticity, $t(76) = -1.346$, $p = .182$.

Projected Demand and Future Cannabis Use

We examined if projected future cannabis demand predicts future cannabis use frequency. Table 5 provides findings from linear regressions of projected T2 demand predicting T2 cannabis use frequency. Findings from the five unadjusted models demonstrated that projected T2 intensity was a statistically significant positive predictor of cannabis use frequency at T2 ($p = .005$), and projected T2 P_{max} was a statistically significant negative predictor of cannabis use frequency at T2 ($p = .003$). When CUD symptoms at T1 were added to the five independent adjusted models, projected T2 intensity was still a statistically significant positive predictor of observed T2 cannabis use frequency ($p = .023$), and projected T2 P_{max} ($p < .001$) and projected T2 breakpoint ($p = .035$) were statistically significant negative predictors of observed T2 cannabis use frequency. However, when cannabis use frequency at T1 was added to the five independent adjusted models, none of the projected T2 measures were significant predictors of future cannabis use frequency.

Given our contrasting results on projected future demand and observed future use, we assessed the associations between projected future demand latent factors and future use. Projected future Persistence was calculated as the mean of the standardized projected T2 O_{max}, P_{max}, breakpoint, and elasticity (reversed) scores. Projected future Amplitude was calculated as the mean of the standardized projected T2 intensity scores, as in Aston et al. (2017). Results of linear regressions indicate that projected future Amplitude was a statistically significant positive predictor of cannabis use frequency at T2 after accounting for baseline CUD symptoms (Standardized $\beta = .244$, $R^2 = .308$, $p = .015$). In addition, projected future Persistence was a statistically significant *negative* predictor of cannabis use frequency after accounting for baseline CUD symptoms (Standardized $\beta = -.213$, $R^2 = .293$, $p = .034$).

Table 5. *Linear Regressions of Projected T2 Demand Predicting Future Cannabis Use Frequency at T2*

Projected T2 Demand	Std. β	Unstandardized B	*p*	R^2
Outcome: Timeline Follow-Back at T2				
Unadjusted Model				
Intensity	.318	10.921	.005**	.101
O_{max}	.010	.345	.088	.000
P_{max}	-.336	-14.690	.003**	.113
BP_1	-.148	-5.816	.198	.022
Elasticity (α)	-.072	-74.664	.533	.005
Adjusted for Timeline Follow-Back at Time 1				
Intensity	.156	5.345	.068	.507
O_{max}	.045	1.541	.587	.487
P_{max}	-.157	-6.871	.068	.507
BP_1	-.048	-1.888	.569	.487
Elasticity (α)	-.075	-77.260	.371	.490

Adjusted for Cannabis Use Disorder Symptoms at Time 1				
Intensity	.230	7.883	.023*	.300
O_{max}	-.116	-3.942	.262	.262
P_{max}	-.343	-15.009	<.001**	.366
BP_1	-.212	-8.318	.035*	.293
Elasticity (α)	.040	41.562	.698	.251

Note. Demand indices were log-transformed. All predictor variables were entered into separate models. $*p < .05$, $**p < .01$. $n = 77$

DISCUSSION

Current Demand and Future Cannabis Use

Based on existing research showing associations between cannabis demand and concurrent (Aston et al., 2016a; Strickland et al., 2017) and future (Aston et al., 2023) consumption, our first aim was to examine the associations between current cannabis demand and future cannabis use in young adults who use cannabis. Our results indicated that observed T1 intensity was a positive predictor of T2 cannabis use frequency (i.e., TLFB past-month use days), even after accounting for T1 CUD. This indicates that higher reported consumption of free (i.e., $0.00) cannabis in the present is associated with more frequent cannabis use in the future. Previous literature demonstrates that alcohol demand intensity, one of the most key demand measures, predicts future alcohol use frequency beyond what can be accounted for by baseline use severity (i.e., AUDIT; Strickland et al., 2019). Alcohol demand intensity also predicts subsequent drinking quantity in the short-term (i.e., same day, Aston & Merrill, 2023) and in the long-term (i.e., 4 years, Gaume et al., 2022). Cannabis demand intensity is also associated with more frequent cannabis use 6 months later, with intensity being the only cannabis demand measure to demonstrate prospective validity (Aston et al., 2023). However, our more unexpected finding is that P_{max} was a negative predictor of future cannabis use frequency. This suggests that reporting lower prices at which the most amount of money on cannabis is spent is associated with more frequent cannabis use in the future, which is inconsistent with previous evidence of P_{max} being related to greater future cannabis use (Aston et al., 2023).

We explored these findings further by examining associations of current Amplitude (ad libitum consumption) and Persistence (consumption despite price increases) factors with future cannabis use. Findings indicated that Amplitude (specifically intensity of demand) was a significant positive predictor of future cannabis use, but Persistence was not a significant predictor of future cannabis use. Given that P_{max} was the only Persistence measure that was a predictor on its own, the result is consistent with previous knowledge that P_{max} may be a poor predictor of substance use outcomes (Zvorsky et al., 2019). Intensity appears to be the most informative current cannabis demand measure for predicting future use. Given the clinical and public health concern of cannabis use in young adults (Figueiredo et al., 2020; Grant et al., 2012; NSDUH, 2022; Patel & Amlung, 2019), these results provide valuable information on their consumption behaviors. Specifically, if future frequency of cannabis use days (this study's outcome variable) is the primary outcome of clinical concern, then present consumption at no or low cost is likely the best MPT predictor. In contrast, degree of sensitivity to price increases does not appear to be an effective predictor. We note that while current intensity/Amplitude predicted future cannabis use even accounting for current CUD symptom count, it did not remain a significant predictor for future cannabis use after controlling for current cannabis use. This suggests that current cannabis use is at least an equally effective predictor of future cannabis use as current intensity, and that studies that examine cannabis use longitudinally should consider the value-added of tasks like the MPT beyond a measure as straightforward as current use.

Projected Future Demand

Our second aim was to explore the novel construct of projected future cannabis demand. Our results revealed that young adults projected higher future expenditure on cannabis (i.e., higher O_{max}) and a relatively inelastic demand. These results demonstrate that young adults expect diminished sensitivity to cannabis price increases in the future relative to their current selves, which is partially consistent with the previous evidence of young adults projecting future increases in alcohol demand across all measures (Kurnellas et al., 2025). The previous study on projected future alcohol demand only included young adults who specifically engage in *heavy* drinking, which might explain their expected future increases across all demand measures, compared to our current participants with *any* presence of past-month cannabis use only projecting future increases in some measures.

We also observed that young adults were relatively accurate in their projections of all five future demand measures. Specifically, projected future and observed T2 demand for all metrics did not significantly differ, and all *projected* change and *observed* change variables were significantly correlated, further indicating relative accuracy of future projections. Kurnellas et al. (2025) previously found that young adults with heavy alcohol use were also relatively accurate in their projections of future demand measures, other than overestimating their future O_{max}. Cannabis use is shown to be relatively stable over time (i.e., 6 months; Aston et al., 2023), which is consistent with our study (TLFB T1 M = 15.03, SD = 9.9; TLFB T2 M = 14.9, SD = 10.1), while alcohol use might exhibit greater variability (Goldman et al., 2011). Ultimately, our results indicate that young adults have a generally sound estimation of their cannabis demand for 3 months into the future.

Based on existing evidence that projected future alcohol demand is associated with subsequent consumption (Aston & Merrill, 2023; Kurnellas et al., 2025), we also examined the associations between projected future cannabis demand and future cannabis use. Our results revealed that projected future intensity positively predicted future cannabis use, where projecting higher consumption of free (i.e., $0.00) cannabis in the future is associated with more frequent cannabis use in the future. This finding is consistent with previous literature on the association between projected future alcohol demand intensity and future consumption (Kurnellas et al., 2025) but even further supports the utility of cannabis demand intensity (Aston et al., 2023) given its *unique* associations (i.e., beyond what can be explained by cannabis use severity) not shown with alcohol. However, our more unexpected finding is that projected future P_{max} and breakpoint were negative predictors of future cannabis use frequency, where projecting lower prices at which 1) maximum expenditure on cannabis and 2) suppression of consumption occur is associated with more frequent cannabis use in the future. We note that, like the analyses of present demand predicting future use, significant findings were preserved when accounting for current CUD symptoms, but not after accounting for current cannabis use.

We further explored these findings by examining projected future Amplitude and Persistence factors' associations with future cannabis use. Projected future Amplitude was a significant positive predictor of future cannabis use frequency, where expecting greater future consumption unrestricted by price is associated with more frequent cannabis use in the future. This finding is consistent with factor analysis showing that higher Amplitude (only intensity for cannabis) was associated with more frequent use (Aston et al., 2017). Additionally, projected future Persistence was a significant negative predictor of future cannabis use frequency, where expecting decreased consumption in the face of price increases in the future is associated with more frequent cannabis use in the future. Previous factor analysis revealed that higher Persistence is associated with lower expectancies of negative cannabis outcomes (Aston et al., 2017), which may be attributable to expected tolerance to acute effects of cannabis long-term (Volkow et al., 2014), but may also be attributable to expectations of lower cannabis risk. This existing work broadly supports other evidence showing associations between higher Persistence and lower perceptions of cigarette-related risks (O'Connor et al., 2016). This is particularly problematic, as the perception of lower cannabis risk is shown to reflect a higher likelihood of risk behavior (e.g., driving after consuming cannabis; Aston et al., 2016b). Therefore, it is possible that an expectation of high price sensitivity (i.e., cannabis use that is responsive to increasing costs, including negative

consequences) might be indicative of a misinformed belief that current cannabis use is unlikely to result in future escalation of use or development of problematic use; this belief may then result in increased vulnerability to subsequent escalation of use. Overall, results on the predictive validity of the projected future demand measures suggest that projected future intensity and price sensitivity (i.e., O_{max}, P_{max}, breakpoint, elasticity) may serve distinct purposes in understanding the trajectory of cannabis use in young adults.

Limitations and Future Directions

Despite potentially valuable contributions to the knowledge on this high-risk population, we note some limitations and future directions. Specifically, the generalizability of the findings is limited to our sample's demographics (i.e., primarily White young adults who attend college), including the legal status of cannabis (legal only for medicinal purposes). In addition, our MPT constrained participants to one cannabis product (joint) and route of administration (smoking), and future research might consider using an adaptive MPT (Bush et al., 2023) to increase the individual-level relevance of the task. We note that four participants (all female) reported that their only current route of administration was oral/concentrates. As this would not rule out familiarity with cannabis hits, and their data were consistent with sample observations while meeting systematicity thresholds, their data were retained in our analyses. We also did not collect a number of measures (e.g., reasons for use, disposable income, consumption quantity) that might contribute to expectations of future use, and thus projected future demand. Additionally, research should measure projected future demand across longer time periods, as substance use is shown to vary in accordance with time of year, academic requirements, and holidays in emerging adults (Goldman et al., 2011). Finally, it is important to note that for both current demand and future projected demand, none of the demand indices predicted future cannabis use after accounting for current cannabis use. While this does not completely undermine the potential utility of the (current and projected future) demand measures of the current study, it does highlight that baseline measures of substance use should be included in longitudinal analyses of use/consequences in order to assess the value-added of novel assessments or constructs.

Conclusion

The present study is the first to examine the predictive utility of cannabis demand in young adults, as well as introduce the novel construct of projected future cannabis demand. The measure of current cannabis Amplitude (i.e., intensity), and measures of projected future cannabis Amplitude and Persistence, predict cannabis use frequency in the future, even accounting for current CUD symptoms. Given this evidence that some projected future demand measures are not wholly redundant with measures of current demand, we believe further research on projected future demand may contribute to both theoretical and practical insights into factors that contribute to the escalation of cannabis use and negative use-related consequences. While in need of further replication, the present results suggest that cannabis-using young adults exhibiting projections of high future Amplitude or low Persistence may benefit from targeted interventions that seek to lower the reinforcing value of cannabis or highlight the decrease in price sensitivity that often accompanies continuation/escalation of cannabis use.

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