Title
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Journal
Psychology of Addictive Behaviors, 37(8)

ISSN
0893-164X

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Publication Date
2023-12-01

DOI
10.1037/adb0000916

Peer reviewed

HHS Public Access

Author manuscript

Psychol Addict Behav. Author manuscript; available in PMC 2024 December 01.

Published in final edited form as:

Psychol Addict Behav. 2023 December ; 37(8): 985–995. doi:10.1037/adb0000916.

Cannabis Demand and Use among Veterans: A Prospective Examination

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Abstract

Objective: Cannabis demand (i.e., relative value), assessed cross-sectionally via a hypothetical marijuana purchase task (MPT), has been associated with use, problems, and dependence symptoms, among others. However, limited work exists on the prospective stability of the MPT. Furthermore, cannabis demand among veterans endorsing cannabis use, and the prospective cyclical relationship between demand and use over time, have yet to be investigated.

Method: Two waves of data from a veteran sample (N=133) reporting current (past 6-month) cannabis use were analyzed to assess stability in cannabis demand over six months. Autoregressive cross-lagged panel models (CLPMs) assessed the longitudinal associations between demand indices (i.e., intensity, O_{max}, P_{max}, breakpoint) and cannabis use.

Results: Baseline cannabis use predicted greater intensity ($ß$ = .32, p<.001), O_{max} ($ß$ = .37, p<.001), breakpoint ($ß$ = .28, p<.001), and P_{max} ($ß$ = .21, p = .017) at 6-months. Conversely, baseline intensity ($ß$ = .14, p=.028), breakpoint ($ß$ = .12, p=.038), and P_{max} ($ß$ = .12, p = .043), but not $O_{max,}$ predicted greater use at 6-months. Only intensity demonstrated acceptable prospective reliability.

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Conclusions: Cannabis demand demonstrated stability over six months in CLPM models, varying along with natural changes in cannabis use. Importantly, intensity, P_{max}, and breakpoint displayed bidirectional predictive associations with cannabis use, and the prospective pathway from use to demand was consistently stronger. Test-retest reliability ranged from good to poor across indices. Findings highlight the value of assessing cannabis demand longitudinally, particularly among clinical samples, to determine how demand fluctuates in response to experimental manipulation, intervention, and treatment.

Keywords

cannabis; marijuana purchase task; demand; behavioral economics; veterans

Introduction

Behavioral economic theory is characterized by the integration of concepts from psychology and economics to study decision-making behavior (Bickel et al., 2014) and may be applied to the study of substance use wherein key elements include substance value juxtaposed against substance cost (i.e., demand). Demand is the quantitative characterization of the relationship between consumption and cost, and is a robust indicator of how valuable a substance is perceived to be for a given individual (Bickel et al., 2011, 2014). Substance demand is highly associated with level of substance use, substance-related problems, and number of dependence symptoms, among others (Aston & Meshesha, 2020; Kaplan et al., 2018; Reed et al., 2020).

Assessment of Demand

Substance demand may be measured by utilizing operant responding procedures in the laboratory wherein individuals respond for rewards at increasing price levels (Hodos, 1961); in this context, by assessing willingness to purchase substances at escalating levels of cost and/or consequences. Alternatively, substance demand may be assessed via utilization of a hypothetical purchase task in which individuals indicate how much of their preferred substance they would be willing to purchase hypothetically at escalating levels of price (MacKillop & Murphy, 2013; Plebani et al., 2012). One key benefit of using a substance purchase task is the ability to study substance value in certain populations for whom actual drug administration would be hazardous, problematic, or illegal. As such, hypothetical purchase tasks have many benefits compared to traditional operant procedures, including ability to assess substance value within treatment-seeking or dependent samples (Meshesha, Aston, et al., 2020), among adolescents whose age might preclude participation in laboratory drug administration research (Murphy et al., 2011), and among Veteran samples (Dennhardt et al., 2016), for whom substance demand may differ due to high rates of use for medical purposes (e.g., sleep, pain, post-traumatic stress disorder; (Metrik, Jackson, et al., 2016; Metrik et al., 2018, 2020). In this regard, hypothetical purchase tasks exist for a multitude of substances, including alcohol (Murphy & MacKillop, 2006), tobacco (MacKillop et al., 2008), electronic cigarettes (Cassidy et al., 2017), opiates (Strickland et al., 2019), and cannabis (Aston et al., 2015, 2021). Moreover, several studies have demonstrated strong concurrence between certain hypothetical tasks against performance in the laboratory for actual substances (Amlung et al., 2012).

From hypothetical purchase tasks, five indices of demand representative of different components of value can be obtained. These include intensity (i.e., consumption at zero cost), O_{max} (i.e., maximum expenditure), P_{max} (i.e., price corresponding to O_{max}), breakpoint (i.e., price at which consumption is suppressed to zero), and elasticity (i.e., slope or change in consumption relative to increase in price). Together, these indices describe a broad range of decisions pertaining to perceived substance value and maintenance of purchase despite escalating cost and consequence.

Stability and Change in Demand

While typically considered to be trait-based, purchase task indices have the propensity to change over time in response to internal and external influences (Acuff et al., 2020), including stress (Amlung & MacKillop, 2014; Owens et al., 2015), experimental manipulation (Amlung et al., 2015; MacKillop et al., 2012; Metrik, Aston, et al., 2016), and even modifications to the instructional set such as alteration in time constraints (Kaplan et al., 2017) or level of next-day responsibilities (Skidmore & Murphy, 2011). However, in the absence of manipulation, purchase task performance has displayed robust stability over time. For example, tobacco demand assessed via the cigarette purchase task displayed stability over one week among a small community sample of individuals who endorsed tobacco use (Few et al., 2012). Additionally, alcohol demand assessed via the alcohol purchase task displayed stability over two weeks among a sample of college student drinkers (Murphy et al., 2009). Results across studies have suggested that all demand indices display good temporal stability with the strongest stability over time for intensity and O_{max}. Further, Acuff and colleagues examined stability of alcohol demand over one month using a variety of demand-related indices (Acuff & Murphy, 2017). Results suggested relatively good temporal stability of the alcohol purchase task over time. Of note, changes in alcohol demand appeared to be closely related to reported changes in alcohol consumption, suggesting that these constructs influence each other in a cyclical manner. Thus, as substance consumption increases or decreases, so too does demand. However, the predominant direction of effect between substance use and demand has not been examined. Thus, while cross-sectional studies and limited prospective work consistently show strong relationships between certain indices of demand and substance use, the strength of those bidirectional pathways over time is unknown (i.e., does demand at baseline better predict substance use at follow-up or vice versa).

Previous work by Strickland and colleagues (2019) examined the temporal reliability of cannabis demand among individuals endorsing opiate use. Findings suggested that cannabis demand had fair to good test-retest reliability at 1-month follow-up, with O_{max} displaying the strongest reliability over time. Strickland and colleagues noted that the absence of inclusion criteria for cannabis use may have contributed to greater variability in cannabis demand over time, potentially due to participants being more vulnerable to internal (e.g., state) and external (e.g., contextual) influences on demand for cannabis. Consequently, it is possible that test-retest reliability for the MPT may be stronger among those who endorse relatively recent cannabis use. Further investigation of the stability of this task is critical, as cannabis use and purchase behaviors are quite complex. Cannabis is considered to be an illicit substance in many states, resulting in substantial variability in availability, price, quality, and potency, among a host of other variables that have been shown to impact cannabis demand (Amlung et al., 2019; Amlung & MacKillop, 2019; Aston et al., 2021; Aston & Meshesha, 2020; Vincent et al., 2017).

The majority of studies examining demand for cannabis tend to recruit samples who endorse fairly regular use. Acuff and colleagues (2017) suggest that with respect to the alcohol purchase task, the temporal stability of alcohol demand for less frequent drinkers may be differentially affected by external influences and environmental changes (e.g., their demand may be more susceptible to change over time due to less stable patterns of use). Despite this, assessment of cannabis demand among those who use cannabis less frequently is less common in the purchase task literature. Individuals who endorse less frequent cannabis use in particular may be more susceptible to external influence, though the direction of influence on demand (i.e., increase or decrease) is currently unknown. One recent investigation assessed whether cannabis demand assessed prior to the initiation of the COVID-19 pandemic among those endorsing any cannabis use in the past three months, likely contributing to sample heterogeneity in use patterns, was a significant predictor of changes in cannabis use and problems during the first 30 days of the COVID-19 state of emergency (Vedelago et al., 2022). However, prospective reliability in demand was not assessed in this study, thus cannabis demand reliability in samples with more heterogeneous use patterns across participants remains unclear.

Similarly, cannabis demand has also gone unexamined in veteran samples. Veterans report increasingly favorable attitudes toward cannabis (Wilkinson et al., 2016), and of those who endorse past-year cannabis use, use for medical purposes is more than double that of the general United States population (Davis et al., 2018). Research suggests that some veterans use cannabis as a substitute for other prescribed and non-prescribed medications (Metrik et al., 2018), and often perceive cannabis to be less harmful than other medications, including opioids (Krawitz, 2015). Veterans are using cannabis at high rates, and may be doing so to combat service-related issues such as posttraumatic stress disorder, traumatic brain injury, anxiety, and depression (Metrik et al., 2018, 2020; Metrik, Jackson, et al., 2016), despite some research indicating that cannabis may actually worsen long-term outcomes such as posttraumatic stress disorder (Metrik et al., 2020). Consequently, investigation of cannabis demand among this population, particularly with a focus on prospective associations with cannabis use patterns, has been hitherto unexamined, though remains critical. Substance demand has been a significant predictor of pharmacological and therapeutic treatment response (Secades-Villa et al., 2016; Mackillop & Murphy 2007), and therefore has particular utility for veteran samples for whom use of cannabis for medical purposes is widespread.

Present Study

The present investigation sought to examine relatively long-term temporal stability of demand for cannabis among Veterans who reported current (past 6-month) use of cannabis. Due to the bidirectional relationships between demand and use, we probed alternative directions of effects between indices of cannabis demand and cannabis use level over time. We analyzed two waves of data from a sample of veterans deployed post-9/11/2001

(Metrik et al., 2020). Our primary goal was to assess stability of cannabis demand over six months, and to examine if and how demand may be altered over time with natural changes in cannabis use in a sample with a substantial range of cannabis use patterns, from infrequent to daily. Specifically, we aimed to determine whether cannabis demand and use frequency influenced one another over time. Moreover, we aimed to determine the predominant direction of effect between cannabis use and demand by contrasting the two possible pathways (i.e., does cannabis demand at baseline predict use frequency at 6-months above and beyond the opposing pathway).

Method

Sample and Procedure

Participants ($N = 361$) were recruited from a Veteran's Health Administration (VHA) facility in the Northeast region of the United States by utilizing the VHA Operation Enduring Freedom, Operation Iraqi Freedom, and Operation New Dawn (OEF/OIF/OND) Roster, an accruing database of combat veterans who recently returned from military service in Iraq and Afghanistan and were enrolled in VHA (Metrik, Jackson, et al., 2016). Participants completed a prospective study examining cannabis use and affective disorders in returning OEF/OIF/OND veterans who were deployed post 9/11/2001 and who reported lifetime cannabis use.

Veterans were screened for eligibility by telephone and were invited for a baseline visit, during which they provided written informed consent and completed a battery of interview and self-report assessments. The baseline session was followed by two additional visits with parallel assessments at 6 and 12 months. The current investigation focuses on data from the baseline and 6-month sessions as MPT data were not collected at 12 months due to a deliberate reduction in the number of measures to reduce final session length. Participants were included in the current study sample if they reported past 180-day cannabis use at either baseline or 6-months, and completed the MPT at both time points ($n = 133$). The study was approved by the university and local VHA institutional review boards. Participants were compensated $50 per visit.

Transparency and Openness

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study. Materials and analysis code for this study are available by emailing the corresponding author. Data were analyzed using Mplus version 8.2 (Muthén & Muthén, 2017). The study design and its analysis were not pre-registered.

Measures

Demographics.—Age, sex, race, ethnicity, marital status, and income were verified through the VHA medical record.

Time-Line Follow-Back.—The Time-Line Follow-Back Interview (TLFB; (Dennis et al., 2004; Sobell & Sobell, 1992) was used to assess past-6-month patterns of cannabis and other substance use. The TLFB has high test–retest reliability and stability over periods of 180

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days (Carey, 1997) and up to one year (Sobell & Sobell, 1992). Days of cannabis use in the 180 days prior to each assessment was used in the present analyses.

Marijuana Purchase Task.—The Marijuana Purchase Task (MPT; (Aston et al., 2015) was developed to assess behavioral economic marijuana demand based on Jacobs and Bickel's procedure (Jacobs & Bickel, 1999) and validated alcohol (Murphy & MacKillop, 2006) and tobacco (MacKillop et al., 2008) purchase tasks. The MPT assessed how many marijuana hits one would smoke at 22 escalating prices ($0 to $10 per hit). Participants were asked to respond to items as if it were a typical cannabis use day and were informed that the cannabis available for purchase was of average quality. Four observed indices (i.e., intensity, breakpoint, O_{max}, and P_{max}) were generated from the MPT.

Data Analytic Strategy

Demand data cleaning and preparation.—As the majority of work on substance demand includes demand assessment at one timepoint (i.e., cross-sectional), participants are normally removed prior to generation of demand indices for violating certain purchase task performance conventions (e.g., trend, bounce, reversal from zero) and are required to report at least two continuous price points to generate elasticity in particular (Stein et al., 2015; Koffarnus et al., 2015). However, elasticity was not generated in the current investigation in an effort to retain participants who reported zero, low, or constant (i.e., purchase of the same amount across escalating price), cannabis demand. The analytic sample used herein included participants with one reversal (baseline: $n = 6$; 6-months: $n = 4$), two reversals (baseline: $n = 2$; 6-months: $n = 0$), zero demand (baseline: $n = 29$; 6-months: $n = 26$), demand for cannabis only at zero cost (baseline: $n = 13$; 6-months: $n = 14$), and constant demand (baseline: $n = 8$; 6-months: $n = 6$). Importantly, no participants failed Stein's (2015) bounce (i.e., frequent price-to-price increases in consumption) or reversal from zero (i.e., positive value after a reported zero) criterion at either timepoint. As participants with zero, low, or constant demand were retained in the analytic sample, Stein's trend (i.e., overall reduction in responding) criterion is not appropriate for evaluating these data. Procedures for cleaning raw demand data were subsequently applied to the sample ($n = 133$) at both baseline and 6-months. Raw data were examined for outliers using standard scores, with a criterion of $Z = 3.29$ to retain maximum data. A small number of outliers were detected in the baseline dataset (59 outlying data points; 2.0%). In addition, a small number of outliers were detected in the 6-month dataset (80 outlying data points; 2.7%). The outliers were determined to be legitimate high-magnitude values and were recoded as one unit higher than the next lowest non-outlying value (Tabachnick & Fidell, 2000). As the distribution for breakpoint and intensity variables were kurtotic at both timepoints, square root transformations were used to obtain normal distributions.

Of note, we elected to retain individuals in our analyses who reported zero demand at either time point, providing they reported at least some cannabis use in the past 6 months at either time point. Specifically, a subset of participants reported zero demand at baseline ($n = 19$), 6-months ($n = 16$), or both ($n = 10$), often corresponding to no cannabis use during that time-period. As such, elasticity was not derived in order to retain this subsample in demand analyses, consistent with prior work examining demand over time (Meshesha, Aston, et al., 2020). Inclusion of individuals with zero demand precluded our ability to generate elasticity for these individuals and for the full sample, thus that particular demand index is not included in the current study. However, the importance of utilizing the full sample outweighed the cost of losing the ability to examine elasticity, particularly due to the importance of allowing demand to decline to zero over time, or rise from zero over time. This technique has been used in clinical demand research (Meshesha, Aston, et al., 2020), wherein the goal is to reduce substance use, likely paired with a reduction in demand. Often individuals with zero demand are removed from demand analyses due to our inability to model a curve without two datapoints (Stein et al., 2015). Because of this, meaningful zeros may be lost, particularly if the research question involves the ability of demand to be mutable or stable.

Cross-lagged models.—Prospective bidirectional relations between each cannabis demand index and cannabis use frequency were examined using cross-lagged panel models (CLPM). Specifically, we aimed to determine the predominant direction of effect between demand and cannabis use (i.e., does cannabis demand at baseline predict use frequency at 6-months and vice versa), as well as whether cannabis demand and use frequency influence one another over time. This approach also allowed us to determine the stability of cannabis demand and use frequency over six months by modeling autoregressive paths (Hamaker et al., 2015).

All CLPM analyses were conducted in Mplus version 8.2 (Muthén & Muthén, 2017). No modeling constraints (e.g., constraining cross-lagged paths) were imposed in CLPMs in the present study. Full information maximum likelihood was used to estimate missing data. Comparative fit index (CFI) and root mean square error of approximation (RMSEA) were used to examine model fit, such that a CFI approaching one and RMSEA approaching zero indicated good fit to the data. Chi-square for each model is presented but was not used to evaluate model fit, due to its sensitivity to sample size (Siddiqui, 2013).

Additional temporal reliability and stability tests were conducted. Initially, test-retest reliability using Pearson correlations were conducted with the full sample as well as separately for three groups of participants who increased, decreased, or remained stable in their cannabis use days from baseline to 6-months. To determine the grouping categories, a change score was computed by subtracting the number of cannabis use days at baseline from the number of cannabis use days at 6-months. Subsequently, the percent change was computed by dividing by the change score from baseline. Participants with more than 20% reduction in use days were categorized as Decreasers, participants with less than 20% change in cannabis use days were categorized as Stable due to the minimal variation in use frequency, and those who increased their use days by 20% or more were considered Increasers. Although there is no set standard for grouping classifications, similar approaches have been used previously (Acuff & Murphy, 2017). Finally, demand stability from baseline to 6-months was evaluated via examination of pre-post comparisons using paired sample t-tests.

Results

Demographic and descriptive statistics of the sample are presented in Table 1. Correlations among demographic variables, cannabis use days, and demand indices are presented in Table 2. Significant bivariate correlations among study variables were used to guide covariate selection for each model. The model with intensity included income as a covariate; breakpoint and P_{max} models included age as a covariate; given socio-demographic variables were not correlated with O_{max} at baseline or 6-months, the O_{max} model did not include covariates. Models with and without identified covariates were compared and findings remained unchanged (see Table 4); thus, we report results from the more parsimonious models without covariates. Model fit for both sets of models (with and without covariates) are reported in Table 3.

Cross-Lagged Panel Models

Four cross-lagged panel models, one for each demand index (intensity, O_{max}, breakpoint, and P_{max}), were evaluated with cannabis use days (see Figure 1). Less than optimal model fit determined by RMSEA was observed for the intensity model that included income as a covariate, though the CFI indicated excellent fit (CFI = .975; RMSEA = .145, 90% CI [.046, .261]; $|^2$ = 226.31(7), $p < .001$). Removal of income resulted in an improved model fit (CFI = 1.000; RMSEA = .000, 90% CI [.000, .000]; $|^2$ = 222.20 (5), $p < .001$) while retaining similar findings.

Intensity.—The intensity model displayed a significant cross-lagged path such that baseline cannabis use days predicted greater intensity at 6-months (ß = .32, $p < .001$). The reverse was also significant, such that baseline intensity predicted more cannabis use days at the 6-month assessment (ß = .14, $p = .027$). Both cannabis use and intensity exhibited strong, positive autoregressive paths from baseline to 6-months, suggesting significant stability in these constructs over time. Residual covariances for intensity and cannabis use were positive and statistically significant, further supporting the relation between intensity and cannabis use at each wave (see Table 4).

$O_{max.}$ The O_{max} model indicated good fit (see Table 3). Findings from the cross-lagged path for the model with O_{max} suggest that baseline cannabis use days significantly predicted greater O_{max} at 6-months (ß = .37, $p < .001$) whereas the reverse was not significant. Both cannabis use days and O_{max} exhibited positive and statistically significant autoregressive paths from baseline to 6-months, suggesting stability in these constructs over six months. Residual covariances for O_{max} and cannabis use days were positive and statistically significant, further supporting the relation between O_{max} and cannabis use days at baseline and 6-months (see Table 4).

Breakpoint.—The models with breakpoint indicated good fit (see Table 3). The cross-lagged path for breakpoint indicated that baseline cannabis use days significantly predicted greater breakpoint at 6-months (ß = .28, $p = .001$). The reverse was also significant, such that baseline breakpoint predicted more cannabis use days at 6-months (ß = .12, $p = .032$). Cannabis use days and breakpoint exhibited positive and statistically significant autoregressive paths from baseline to 6-months, again indicating stability over six months.

Residual covariances for breakpoint and cannabis use days were positive and statistically significant.

$P_{max.}$ The cross-lagged path with P_{max} suggested that baseline cannabis use days significantly predicted greater P_{max} at 6-months ($ß$ = .21, p = .017). The reverse was also significant, such that baseline P_{max} predicted more days of cannabis use at 6-months ($ß$ = .12, p = .043). Cannabis use days and P_{max} exhibited positive and statistically significant autoregressive paths from baseline to 6-months, again indicating demand stability over six months. Residual covariances for P_{max} and cannabis use days were positive and statistically significant at baseline but not at 6-months.

Reliability and Stability

Test-retest reliability for demand indices from baseline to 6-months for the full sample were as follows: r =.736 (intensity), r = .581 (O_{max}), r = .544 (breakpoint), and r = .461 (P_{max}). Among participants who decreased their use days, test-retest results were inadequate: r =.047, r = .370, r = .202, and r = .280, for intensity, O_{max}, breakpoint, and P_{max}, respectively. Among participants whose use days remained stable, test-retest results were similarly inadequate: r =.247, r = −.132, r = −.001, and r = .247, for intensity, O_{max}, breakpoint, and P_{max}, respectively. Among participants who increased their use days, test-retest results ranged from acceptable to inadequate: r =.717, r = .50, r = .617, and r = .308, for intensity, O_{max}, breakpoint, and P_{max}, respectively. Specific descriptives on differences in cannabis use days and demand indices between the three groups can be found in Table 5.

Paired sample t-test analyses evaluating pre-post demand stability from baseline to 6months for the full sample suggested relative stability with no significant differences between the two assessment time points. Specifically, results indicated the following for intensity, O_{max}, breakpoint, and P_{max}: t_{132} = −.195, p = .846, d = .01, dz = .02; t_{132} = −.465, p = .643, d = .04, dz = .04; t_{132} = .351, p = .726, d = .03, dz = .03; t_{132} = .841, p = .402, d =.12, dz = .07, respectively.

Discussion

The current investigation represents the first study to examine the bidirectional relations between demand indices and cannabis use frequency over time, and added to the limited literature regarding temporal stability of MPT indices. In support of our hypotheses, demand indices were stable over time. Moreover, cannabis use at baseline predicted higher demand at 6-months and vice versa, with the exception of O_{max}, after accounting for stability (i.e., autoregressive paths), reflecting bidirectional relations between use and demand over time. Of note, compared to the opposite pathway, we observed consistently stronger prospective relationships from cannabis use to demand across all four examined indices, suggesting that the predominant pathway of effect is from use to demand rather than demand to use. Thus, the current findings contribute to the cannabis demand literature by supporting the reliability of the MPT indices over a 6-month period of time when assessed in the absence of intervening changes or manipulations. Findings from this study corroborate results in the literature concerning temporal stability of purchase task indices for cannabis (Strickland et al., 2019), alcohol (Acuff & Murphy, 2017; Murphy et al., 2009), and tobacco (Few et al., 2012).

Stability of Cannabis Demand

In the current investigation, all four examined demand indices (i.e., intensity, O_{max}, P_{max}, and breakpoint), as well as cannabis use frequency, exhibited stability when assessed across six months. Thus, in a sample with relatively well-established cannabis use patterns, demand is unlikely to change significantly in the absence of intervention or manipulation. As expected, our findings demonstrate considerable stability in cannabis use in our sample due to the parent study design (i.e., observational) and the relatively brief assessment window, as compared to other methodological (e.g., treatment outcome research) and sampling approaches (i.e., developmental research). Moreover, the full sample in the current study have well-established cannabis use patterns and display less fluctuation compared to younger individuals who use cannabis who may depend more on consistent access, which can be influenced by local availability, employment, and potential legal ramifications. Younger individuals endorsing cannabis use who have been using for comparatively less time may still be experimenting with strains, modes, and formulations (Freeman & Winstock, 2015; Meier, 2017), thus are likely still developing steady use patterns.

Bidirectional Relations Between Demand and Cannabis Use

In addition to stability in both demand and use patterns over time, the current results indicate that cannabis use at baseline predicted higher demand at 6-months and vice versa, with the exception of O_{max}, after accounting for the stability (i.e., autoregressive paths) of these constructs over time. Across all four examined indices, cannabis use prospectively predicting cannabis demand was consistently stronger, indicating that the predominant direction of effect is from use to demand and suggesting that use and experience likely influence changes in demand over time. Still, some demand indices in particular (i.e., intensity, breakpoint, P_{max}) are still useful in the opposing path (i.e., cannabis demand predicting use), and thus may be useful in the prediction of subsequent cannabis use in other longitudinal research. Importantly, these indices may have the propensity to predict treatment response for cannabis use disorder in studies wherein treatment efficacy is a central goal, as has been shown for alcohol (MacKillop & Murphy, 2007).

Although baseline cannabis use predicted greater maximum expenditure (i.e., O_{max}) at follow-up, the reverse was not true. In other words, cannabis use is a robust predictor of the maximum amount an individual is willing to pay for cannabis later in time, however, O_{max} did not significantly predict use at follow-up after accounting for stability over time in this sample. The current sample reported highly variable cannabis use patterns across participants ranging from infrequent use to daily use (i.e., 35% of the sample at baseline), averaging 35% cannabis use days in the past six months. Previous research on cannabis demand has been conducted with more homogeneous samples of individuals reporting very frequent use (e.g., 72% cannabis use days in past 60 days (Aston et al., 2015); 66% of sample reporting daily cannabis use (Collins et al., 2014)). Thus, it is possible that maximum expenditure is not a robust predictor of subsequent use in a heterogenous sample with diverse use patterns. Purchasing patterns for those who use less frequently are likely to be more transient, susceptible to changes in availability, and may even occur less often if individuals primarily use cannabis that has been purchased by friends, roommates, or significant others. Thus, while O_{max} is typically a robust predictor across substances for those who endorse generally frequent use, it may not be ideal for predicting future use in samples with heterogenous use patterns. That being said, the magnitude of the prospective association between use and O_{max} was, while not significant, nearly the same as the magnitude for the other indices (i.e., .12 versus .11). Thus, overinterpretation of this nonsignificant finding may be injudicious; these variables remain correlated with cannabis use at each wave, consistent with existing literature (Aston et al., 2015, 2020; Collins et al., 2014).

The present investigation also included assessment of test-retest reliability of cannabis demand indices, with emphasis on whether change in use over time (i.e., decrease, no change, increase) impacts reliability. Consistent with work on alcohol demand by Acuff and Murphy (2017), reliability of cannabis demand tended to be good in the group who reported an increase in cannabis use days over time. However, reliability was poor in the groups who decreased or remained stable in their number of cannabis use days at 6-months. Of note, the groups who decreased cannabis use or remained stable over time were quite heterogenous in their use levels, which may have impacted reliability of demand. Furthermore, both of these groups exhibited a reduction in their cannabis use days by approximately ten days over time, which may be considered a clinically meaningful reduction in use and demand as these groups reported approximately 11 and 34 use days at baseline, respectively. In contrast, the group who increased their use over time, though exhibiting a larger increase in their use days at 6-months (i.e., approximately 26 days), was likely not experiencing a clinically meaningful increase in their use, as they reported approximately 130 cannabis use days at baseline. These use patterns may have contributed to better reliability in the group who increased use, as compared to the other groups, due to the change in use being less clinically meaningful. Moreover, reliability of P_{max}, regardless of group, was especially low. This is also consistent with previous work on alcohol demand (Murphy et al., 2009; Acuff & Murphy 2017) and aligns with most work that suggests P_{max} may be a poor predictor of key substance use outcomes (e.g., Zvorsky et al., 2019).

Limitations and Future Directions

While the current study makes an important contribution to the cannabis demand literature regarding temporal stability of the MPT, there are important limitations to note. First, this investigation assesses a relatively small sample of participants who use cannabis. Replication of these findings in a larger sample is warranted. Second, demand was assessed at only two time points, albeit the length between time points is noteworthy and speaks to lasting stability, and, potentially, to poorer reliability for demand indices other than intensity. Subsequent research should utilize more time points to assess whether stability is retained over even longer periods, and to capture any potential fluctuations in demand that may have been missed between the two time points included in this investigation. Moreover, here we were limited to assessing between- rather than within-person effects with only two waves of data. Subsequent research should examine cannabis demand over longer intervals of time in an effort to disaggregate between- and within-person effects. Third, this study assessed a sample of predominantly male veterans. Thus, findings reported herein may not generalize to female veterans or non-veteran samples. Fourth, heterogeneity in cannabis use patterns in the current sample may have contributed to poorer reliability for some demand indices. However, if the MPT exhibits stability in a sample that includes a substantial number of individuals who endorse cannabis use less frequently, it follows that those who report heavier use with stable use patterns would likely exhibit stability over time as well. Fifth, the version of the purchase task used in this study included marijuana hits as the unit of purchase. A modified version of the MPT, informed by qualitative research, now utilizes grams as the unit of purchase, and includes an improved instructional set (Aston et al., 2021). Future research should examine cannabis demand over time using the modified measure, which may offer increased index stability due to its superior instructional set which more closely aligns with actual purchase and consumption patterns. Sixth, the nature of CLPM models with this sample size precludes inclusion of all demand indices in a single model, eliminating the ability to better understand the unique nature of each relationship described. Subsequent studies with larger sample sizes that can accommodate inclusion of all demand indices may be able to disentangle the unique influence of each demand index. Finally, the decision to retain individuals in demand analyses with extremely low or zero demand precluded our ability to generate elasticity, as this cannot be achieved in such participants due to demand equation restrictions that exist in the most commonly used equations (e.g., Koffarnus et al., 2015; Hursh & Silberburg 2008). While this decision is a limitation, it is also a strength, as demand must be permitted to rise from or decline to zero in prospective studies. Future prospective demand work may opt to generate elasticity using mixed effects modeling, a novel approach that holds promise and is worthy of investigation in subsequent work (Kaplan et al., 2021).

Purchase tasks are uniquely complex assessments that may display stability over time in the absence of intervening variables, but are also highly susceptible to manipulation in the form of next-day responsibilities (Skidmore & Murphy, 2011), laboratory stress paradigms (Owens et al., 2015), substance cue exposure (Metrik, Aston, et al., 2016), and therapeutic intervention (Meshesha, Soltis, et al., 2020). Thus, while demand remains stable in the absence of manipulation and/or change in substance use, demand has the capacity to be altered by a host of external influences. As such, changes in demand may ultimately be associated with changes in substance use level. Consequently, intervention and prevention efforts that aim to directly impact substance demand may be able to effect more permanent changes in substance use. Future research should continue to assess cannabis demand longitudinally, particularly among clinical samples, in order to examine how demand changes in response to intervention and treatment.

Funding:

Funding for this research was supported by NIDA grant K01DA039311 (Aston), NIGMS COBRE grant P20GM130414 (Aston), NIAAA grant K23AA028269 (Meshesha), NIDA grant T32DA016184 (Stevens), and NIDA grant R01DA033425 (Metrik, Borsari). All funding sources had no other role in study design or manuscript preparation other than financial support. None of the authors have any conflicts of interest to disclose. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health, the Department of Veterans Affairs or the United States Government.

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Public Health Significance:

This study demonstrated that indices of cannabis demand, specifically, intensity, P_{max}, and breakpoint, display bidirectional predictive associations with cannabis use, and across demand indices, the prospective pathway from cannabis use to demand was consistently stronger. Consequently, outcomes from this investigation suggest that prospective assessment of cannabis demand may be particularly valuable within the context of demand fluctuations following manipulation, clinical intervention, and therapeutic treatment.

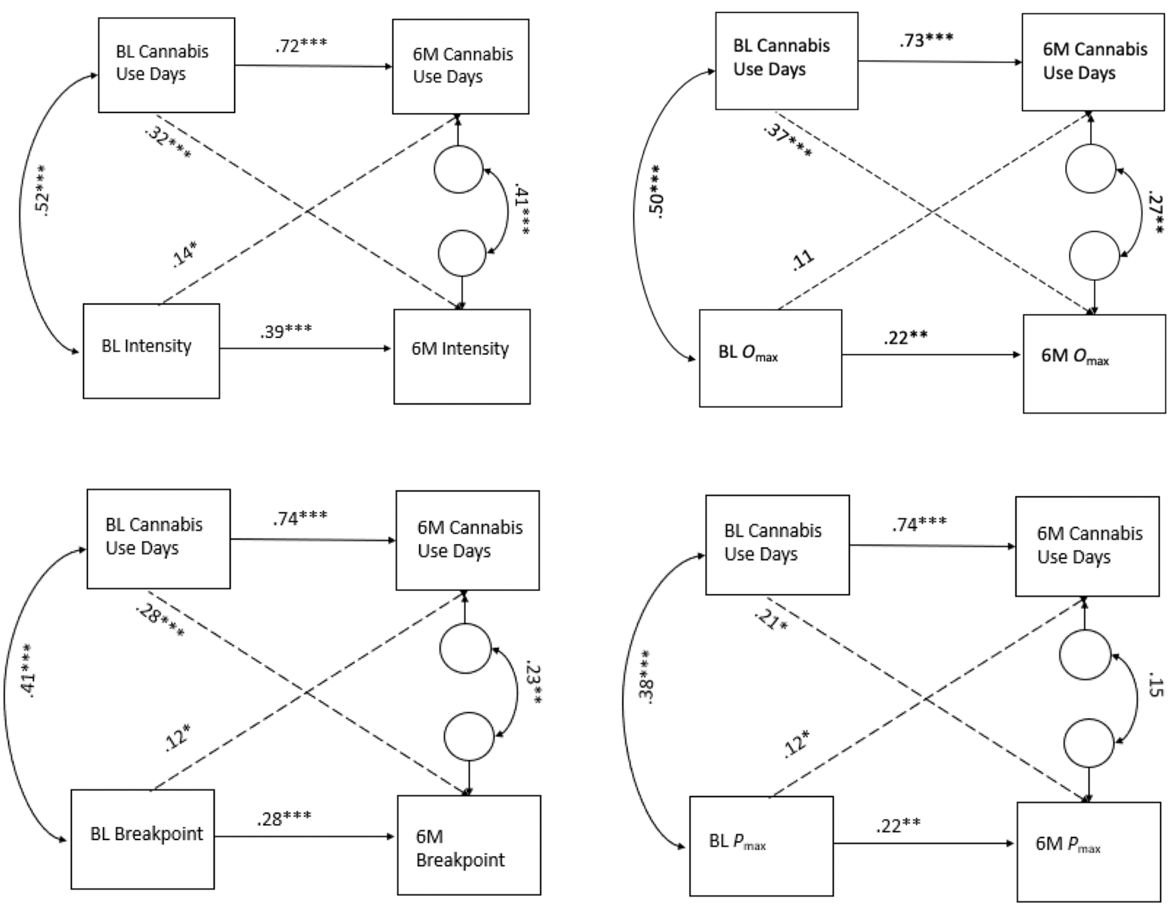

Figure 1.

The four cross-lagged panel math models displaying associations between cannabis use days and intensity, O_{max}, breakpoint, and P_{max} across two time-points (baseline and 6-month assessments). Curved arrows represent correlation between the variables. Solid straight arrows represent the autoregressive paths. Dashed diagonal lines represent the cross-lagged paths. Panel A represents the intensity model; panel B represents the O_{max} model; panel C represents the breakpoint model; and panel D represents the P_{max} model. BL= baseline assessment; 6M = 6-month post-baseline assessment. Model estimates presented are without covariates.

Table 1.

Sample demographics, substance use, and demand

Variable	*n* (%) or *M* (*SD*)
Age	31.09 (*SD* = 7.89)
Sex (%male)	125 (94%)
Ethnicity	
Hispanic/Latino	18 (13.5%)
Race	
American Indian/Alaska Native	1 (0.8%)
Asian	3 (2.3%)
Black or African American	7 (5.3%)
White or Caucasian	101 (75.9%)
Multiracial	7 (5.3%)
Other	12 (9%)
Unknown/Missing	2 (1.5%)
Marital Status	
Single/Never Married	55 (41.4%)
Married/Living with a partner	36 (27.1%)
Divorced/Separated	33 (24.8%)
Unmarried, Living with a partner	9 (6.8%)
Annual Household Income	
$19,999 or less	28 (21.1%)
$20,000 – 39,999	47 (34.5%)
$40,000 – 59,999	29 (21.8%)
$60,000 or higher	29 (21.8%)
Cannabis Use Behavior	
Cannabis use at BL	115 (86.5%)
Cannabis use at 6M	113 (85.0%)
Cannabis use days BL	62.92 (*SD* = 72.49)
Cannabis use days 6M	66.71 (*SD* = 75.53
Daily cannabis use BL	46 (34.6%)
Daily cannabis use 6M	41 (30.8%)
Other Substance Use	
Cigarette smokers at BL	72 (54.1%)
Cigarette use days among smokers	149.63 (*SD* = 52.84)
Alcohol drinkers at BL	122 (91.7%)
Alcohol use days among drinkers	51.65 (*SD* = 52.26)
Cannabis Demand BL	
Intensity	21.43 (*SD* = 33.20)
O_{max}	14.18 (*SD* = 26.23)
P_{max}	2.22 (*SD* = 3.15)
Breakpoint	3.17 (*SD* = 3.67)

Variable	*n* (%) or *M* (*SD*)
Cannabis Demand 6M	
Intensity	21.94 (*SD* = 33.01)
O_{max}	19.63 (*SD* = 48.73)
P_{max}	1.84 (*SD* = 2.68)
Breakpoint	3.04 (*SD* = 3.59)

Note: BL= Baseline assessment, 6M = 6 months past baseline assessment. All substance use frequency reported is past 180 days. Demand indices are presented as raw untransformed values.

Table 2.

Correlations among demographic variables, cannabis use, and observed demand indices at baseline and 6-months

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Age	--													
2. Sex	−.011	--												
3. Race	−.016	−.033	--											
4. Income	.317**	−.132	−.194*	--										
5. BL Cannabis Days	−.052	.122	.205*	−.291**	--									
6. 6M Cannabis Days	−.084	−.028	.13	−.262**	.788**	--								
7. BL Intensity	−.113	.190*	.101	−.257**	.520**	.509**	--							
8. 6M Intensity	−.061	.001	.026	−.301**	.523**	.644**	.556**	--						
9. BL O_{max}	−.063	.099	−.073	−.13	.504**	.481**	.513**	.345**	--					
10. 6M O_{max}	.136	−.07	−.092	−.068	.483**	.538**	.312**	.671**	.408**	--				
11. BL Breakpoint	−.101	.082	−.108	−.106	.410**	.426**	.368**	.314**	.886**	.382**	--			
12. 6M Breakpoint	.189*	−.091	−.132	.03	.397**	.463**	.202*	.494**	.359**	.893**	.395**	--		
13. BL P_{max}	−.112	.039	−.087	−.06	.378**	.396**	.282**	.308**	.809**	.375**	.937**	.390**	--	
14. 6M P_{max}	.233**	−0.1	−.079	.072	.290**	.337**	.074	.364**	.288**	.829**	.319**	.923**	.301**	--

Note:

* $p < .05$,

** $p < .01$;

BL = baseline assessment, 6M = 6-month assessment

Table 3.

Model fit statistics with cannabis demand indices and cannabis use days.

	$\|^2$	*df*	CFI	RMSEA	BIC	AIC	$\otimes\|^2$	$\otimes$*df*	*p*
Models with Covariates [a]									
Intensity	226.31	7	0.97	.145	4218.42	4172.17	7.58	2	.023
Breakpoint	185.55	7	1.00	.000	3735.33	3689.08	1.38	2	.503
P_{max}	167.19	7	1.00	.000	3668.95	3622.70	1.68	2	.432
Models without Covariates									
Intensity	222.20	5	1.00	.000	4212.75	4172.29	0.00	0	.000
O_{max}	183.93	5	1.00	.000	3396.35	3355.88	0.00	0	.000
Breakpoint	173.97	5	1.00	.000	3737.13	3696.66	0.00	0	.000
P_{max}	154.14	5	1.00	.000	3672.22	3631.75	0.00	0	.000

Note: The full model with intensity included income as a covariate, while the models with breakpoint and P_{max} included age as a covariate. Presented herein are model fit statistics with and without said covariates.

[a] Socio-demographic variables were not significantly correlated with O_{max} at baseline or 6-months; thus, this model was not conducted with covariates.

Table 4.

Standardized parameter estimates (standard errors) from cross-lagged panel models examining cannabis demand and cannabis use days in past 180-days

Path	Intensity	O_{max} [a]	Breakpoint	P_{max}
Models without Covariates				
Autoregressive				
BL Cannabis use 6M Cannabis	.72 (.05)***	.73 (.05)***	.74 (.04)***	.74 (.04)***
BL Demand ✇6M Demand	.39 (.08)***	.22 (.08)**	.28 (.08)***	.22 (.09)**
Cross-lagged				
BL Cannabis use ✇6M Demand	.32 (.08)***	.37 (.08)***	.28 (.08)***	.21 (.08)*
BL Demand ✇6M Cannabis use	.14 (.06)*	.11 (.06)	.12 (.06)*	.12 (.06)*
Covariance				
BL Demand/Cannabis Use	.52 (.06)***	.50 (.07)***	.41 (.07)***	.38 (.07)***
6M Demand/Cannabis Use	.41 (.07)***	.27 (.08)**	.23 (.08)**	.15 (.09)
Models with Covariates				
Autoregressive				
BL Cannabis use ✇6M Cannabis	.72 (.05)***	-	.74 (.04)***	.75 (.04)***
BL Demand ✇6M Demand	.37 (.08)***	-	.30 (.08)***	.25 (.08)**
Cross-lagged				
BL Cannabis use ✇6M Demand	.32 (.08)***	-	.28 (.08)***	.21 (.08)*
BL Demand ✇6M Cannabis use	.14 (.06)*	-	.12 (.06)*	.12 (.06)†
Covariance				
BL Demand/Cannabis Use	.52 (.06)***	-	.41 (.07)***	.38 (.07)***
6M Demand/Cannabis Use	.41 (.07)***	-	.25 (.08)**	.18 (.08)*

Note: BL = baseline assessment; 6M = 6 months post-baseline assessment. All substance use frequency reported is past 180 days.

[a]Socio-demographic variables were not significantly correlated with O_{max} at baseline or 6-months; thus, this model was not conducted with covariates.

†p = .051,

*p < .05,

**p < .01,

***p < .001

Table 5.

Mean (SD) for cannabis use days and demand indices across groups who decreased, did not change, and increased their use of cannabis from baseline to 6-months

Variable	Decrease (n = 47) Mean (SD)	No Change (n = 35) Mean (SD)	Increase (n = 50) Mean (SD)
BL Cannabis Use Days	10.77 (26.01)	34.37 (51.52)	129.60 (60.64)
6M Cannabis Use Days	1.15 (1.25)	23.51 (19.34)	156.30 (35.01)
BL Intensity	7.55 (19.97)	15.43 (28.25)	38.90 (38.94)
6M Intensity	3.32 (4.44)	12.37 (21.10)	46.38 (39.97)
BL O_{max}	5.30 (15.93)	12.51 (23.07)	23.04 (30.16)
6M O_{max}	3.37 (6.35)	10.14 (19.76)	32.58 (44.59)
BL Breakpoint	1.41 (2.55)	3.22 (3.73)	4.81 (3.84)
6M Breakpoint	1.47 (2.62)	2.39 (3.11)	4.99 (3.88)
BL P_{max}	0.87 (1.69)	2.33 (3.26)	3.46 (3.64)
6M P_{max}	0.98 (2.13)	1.71 (2.56)	2.76 (2.98)

Note: BL = baseline assessment; 6M = 6 months post-baseline assessment. All substance use frequency reported is past 180 days. Demand indices are presented as raw untransformed values.