Published in final edited form as:

Drug Alcohol Depend. 2020 February 01; 207: 107820. doi:10.1016/j.drugalcdep.2019.107820.

Greater delay discounting and cannabis coping motives are associated with more frequent cannabis use in a large sample of adult cannabis users

Michael J. Sofis^{a,*}, Alan J. Budney^a, Catherine Stanger^a, Ashley A. Knapp^b, Jacob T. Borodovsky^c

^aGeisel School of Medicine, Dartmouth College, Center for Technology and Behavioral Health, 46 Centerra Parkway, Suite 315, Lebanon, NH, USA

^bDepartment of Preventive Medicine, Northwestern University Center for Behavioral Intervention Technologies (CBITs), 750 N. Lake Shore Drive Chicago, IL, 60611, USA

^cDepartment of Psychiatry, Washington University School of Medicine in St. Louis, 660 South Euclid Avenue, Box 8134, St. Louis, MO, 63110, USA

Abstract

Background: Self-regulation deficits expressed through a decreased ability to value future rewards (delay discounting (DD)) and impaired emotion regulation (negative urgency (NU), cannabis coping motives (CCM), and anxiety sensitivity (AS)) relate to more frequent or problematic cannabis use. However, there is a need to better understand how self-regulation and emotion regulation constructs reflect competition between deliberative and reactive systems that drive individual differences in cannabis use patterns. Further, few studies assess frequency of cannabis use within and across days of use, which may obscure differentiation of individual differences.

Methods: In a large national sample of 2545 cannabis users, Latent Class Analysis was used to derive participant sub-classes based on two frequency indices, self-reported cannabis use days and times cannabis was used per day. Three classes emerged: Low (1–9 days/month, 1 time/day; 23 %), moderate (10–29 days/month, 2–3 times/day; 41 %), and high (30 days/month, 4 times/day; 36 %). Relationships among frequency classes and emotional regulation and impulsivity were assessed with a multinomial logistic regression.

Results: Higher frequency use was associated with greater DD ($\chi^2 = 6.0$, $p = .05$), greater CCM ($\chi^2 = 73.3$, $p < .001$), and lower cognitive AS ($\chi^2 = 12.1$, $p = .002$), when controlling for

*Corresponding author at: Center for Technology and Behavioral Health, 46 Centerra Parkway, Suite 315, Lebanon, NH, USA., michael.j.sofis@dartmouth.edu (M.J. Sofis), jborodovsky@wustl.edu (J.T. Borodovsky).

Contributors

AAK, MJS, CS, and AJB conceptualized the study. AAK collected the data, and MJS and JTB performed data analysis. MJS and AJB prepared the manuscript. All authors finalized the manuscript. MJS and AB executed revisions to the manuscript.

Declaration of Competing Interest

None.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.drugalcdep.2019.107820>.

demographics, tobacco use, and number of cannabis administration methods. Frequency class and NU were not significantly associated.

Conclusions: Identifying meaningful patterns of cannabis use may improve our understanding of individual differences that increase risk of frequent or problematic cannabis use. Excessive delay discounting and using cannabis to cope with negative affect may be relevant targets for treatments designed to reduce cannabis use.

Keywords

Cannabis; Marijuana; Delay discounting; Cannabis coping motives; Anxiety sensitivity; Latent class analysis

1. Introduction

The number of individuals who reported past-month cannabis use rose by 55 % in the U.S. between 2002 and 2017, and the percentage of those individuals who used cannabis at daily or near-daily levels increased by 28 % (SAMHSA, 2018). The rise in cannabis use is concerning because it is linked to biopsychosocial impairments characteristic of Cannabis Use Disorder (CUD; Budney, 2006; Hasin et al., 2013; Volkow et al., 2014). Like other substances, cannabis use is thought to be driven by imbalances between a *deliberative* neural system that mediates cognitive control and future valuation, and a *reactive* system that facilitates reward and emotional processes (Kim-Spoon et al., 2019; Lopez-Vergara et al., 2019). This approach posits that maladaptive decisions either occur through failures of self-regulation, the exertion of control (top-down) over reflexive processes to achieve long-term goals (Bickel et al., 2012), or through impaired emotion regulation, the adaptive control of one's emotional processes (bottom-up; Bickel et al., 2018). This “competing systems” framework may help identify individual differences in deficits that interact within and across systems to drive substance use (Bickel et al., 2018; Lopez-Vergara et al., 2019). Despite support for this approach to understanding cannabis use, few studies have examined how psychological constructs of both systems independently or jointly relate to frequent or problematic cannabis use. Testing whether this model translates to cannabis use, may help identify constructs that relate among the two systems and that jointly contribute to the development and maintenance of frequent cannabis use.

One of the more robust indicators of self-regulation (i.e., deliberative system) is the ability to value future rewards in the presence of immediate rewards, known as *delay discounting* (DD; McClure and Bickel, 2014; Yi et al., 2009). DD is assessed by systematically presenting choices between smaller sooner and larger later rewards across a range of reward amounts and delays which tend to elicit the deliberative (prefrontal cortex) and reactive systems (limbic and paralimbic regions), respectively (McClure et al., 2004; Peters and Büchel, 2011). Excessive preference for larger later rewards reflects the ability to inhibit impulses to choose the smaller immediate reward and value the larger, delayed reward (i.e., self-regulation; McClure and Bickel, 2014). Among substance users, excessive DD (impaired future valuation) corresponds to more frequent substance use and misuse (see Amlung et al., 2017) and is impaired in those with a substance use disorder (SUD) relative to controls (see MacKillop, 2013). Interestingly, DD and cannabis-related outcomes have not

consistently demonstrated significant associations across experimental studies (Heinz et al., 2013; Strickland et al., 2017). However, most studies have found that DD is positively associated with cannabis use frequency or problems (Aston et al., 2016; Kim-Spoon et al., 2019; Lopez-Vergara et al., 2019; Patel et al., 2019; VanderBroek et al., 2016), and the observed relationships were of similar effect sizes (small) as those for other substances (Amlung et al., 2017). These small effect sizes suggest that other constructs, like those driven by the reactive system, likely contribute to cannabis use frequency.

The inability to regulate emotions is driven by the reactive system (Hurd et al., 2014) and can be conceptualized as a form of emotion-based impulsivity (Cyders et al., 2014a) or an inability to suppress emotional reactivity (Goldstein and Volkow, 2011). Emotion-based impulsivity that contributes to an inability to regulate emotions is commonly assessed with the construct *negative urgency* (NU), which is characterized by impulsive or rash acts in response to negative affect (Cyders and Smith, 2008). NU, a subscale of the UPPS Impulsive Behavior scale, is conceptualized as one of five independent facets of impulsivity (Whiteside and Lynam, 2001), and relates to cannabis use and other substance use primarily via heightened reward and affective processes that are mediated by excessive reactive system activity (Smith and Cyders, 2016). NU has not been associated with deliberative system brain regions, which suggests that NU likely impacts substance use through a “bottom-up” mechanism. In cannabis users, NU has been linked to distress tolerance (Kaiser et al., 2012), depression symptoms (Pang et al., 2014), and more frequent cannabis use (VanderVeen et al., 2016).

Two prominent emotion regulation constructs that have been used to study emotion reactivity among cannabis users are anxiety sensitivity (AS) and cannabis coping motives (CCM). AS, defined as the fear of the negative consequences of anxiety (Reiss et al., 1986), encompasses a global dimension score and three lower-order dimensions that reflect fear of losing cognitive control (cognitive AS), fear of serious physical illness (physical AS) and belief that certain publicly observable social behaviors will evoke extreme social consequences (Social AS; Brown et al., 2012; Reiss and McNally, 1985; Taylor et al., 2007). AS reflects reactive system activity, but may also relate to deliberative system activity that is activated during DD tasks, reflecting a shared neural network (Otto et al., 2016; Schäfer et al., 2009; Wesley and Bickel, 2014). When presented with fear-provoking images, those with higher AS have been shown to demonstrate greater deactivation of deliberative system regions of the network, potentially reflecting a cognitive control deficit that spans both systems (Schäfer et al., 2009; Wesley and Bickel, 2014). Relative to social and physical AS, cognitive AS (i.e., fear of losing cognitive control) seems most likely to share deliberative system activation patterns. Although few studies have assessed relationships between AS and deliberative system constructs, examining associations among the individual AS dimensions, DD, and cannabis use may help identify which AS dimensions, if any, overlap with DD, thus providing a better understanding of potential two-systems networks that underlie cannabis use and misuse.

Another common emotion regulation construct is using cannabis to cope with negative affect (Cannabis Coping Motives; CCM), which is often assessed using the Marijuana Motives Measure, with CCM being one of five subscales (MMM; Simons et al., 1998). Among past-

month cannabis users, CCM positively relates to frequency of cannabis use (Bravo et al., 2017; Johnson et al., 2010) and cannabis-related problems (Manning et al., 2019; Pearson et al., 2017). Interestingly, cannabis users who demonstrate high levels of AS are more likely to report using cannabis to cope with negative affect (High Cannabis Coping Motives; CCMs) than those low in AS, which may increase susceptibility to develop CUD (Bonn-Miller et al., 2007; Johnson et al., 2010). Using cannabis to cope is thought to be mediated by reactive system activity in response to craving, stress, or other forms of negative affect (Carey et al., 2015; Rodríguez de Fonseca et al., 1997; Zhao et al., 2019). CCM and AS have been shown to positively relate to each other and to cannabis problems (Johnson et al., 2010; Paulus et al., 2017).

Self-regulatory and emotion regulation constructs and their association with cannabis use have primarily been studied separately. Few studies have assessed the joint influence of self-regulatory and emotion regulation constructs on frequency of cannabis use. Evaluating potential relationships among frequency of cannabis use, self-regulation (DD), and both facets of emotion regulation (emotion-based impulsivity (NU)) and emotion reactivity (CCM, and AS-C, AS-P, and AS-S)) provides an initial opportunity to determine whether more frequent cannabis use is associated with processes underlying self-regulation, emotion regulation, or both (i.e., competing systems approach). Evidence that both self-regulation and emotion regulation relate to more frequent cannabis use would provide support for a competing systems framework to understanding cannabis use and could facilitate identification of individualized patterns of deficits that respond differentially to preventive or treatment efforts.

Several limitations of the literature examining associations between cannabis use, self-regulation, and emotion regulation must be addressed to better understand how these constructs relate to cannabis use. For example, most studies include relatively small samples with predominately low levels of cannabis use (Buckner et al., 2007; Kollins, 2003; Moreno et al., 2012). Small samples with lower levels of cannabis use can restrict identification and testing within empirically defined subgroups of users for which these constructs may be most influential. Second, most studies rely on relatively simplistic frequency of use measures to assess use across broad time frames (i.e., annual to daily), which may obscure variability in naturally emergent cannabis use patterns. For example, although number of days of cannabis use appears to be a common metric of frequency of use (Budney et al., 2011; Hasin et al., 2016; Lopez-Vergara et al., 2019), frequency of use within days varies greatly across individuals (Buckner et al., 2015), and would seem important to measure when investigating risk factors related to frequent or problematic use. Approaches that consider days and times per day may enhance the temporal resolution with which cannabis use patterns are identified and help detect meaningful cannabis use subgroups that isolate individual differences in self-regulation and emotion regulation (c.f. Lopez-Vergara et al., 2019). Of note, it is also likely quite important to determine how much cannabis (e.g., THC) is used per episode, unfortunately, a reliable and valid measure for assessing quantity of use over time is not available (Cuttler and Spradlin, 2017; Hindocha et al., 2018).

In this study, social media recruitment methods were used to obtain a large sample of adult cannabis users to determine potential associations among frequency of cannabis use, self-

regulation (DD), and emotion-based impulsivity (NU) and reactivity (CCM, AS-C, AS-P, AS-C) components of emotion regulation. All variables were hypothesized to be positively associated with higher frequency use. An exploratory Latent Class Analysis (Lanza and Rhoades, 2013) was used to potentially identify meaningful subgroups of cannabis users based on frequency of use (times per day and days of use) to isolate individual differences expressed through self-regulation and emotion regulation that increase the risk of frequent cannabis use.

2. Materials and method

2.1. Recruitment

Participants from all 50 U.S. states completed an online survey distributed on Facebook and Instagram through paid advertisements (Borodovsky et al., 2018). Individuals who used cannabis were targeted by using cannabis-related imagery and language in a Facebook advertisement displayed to those who previously endorsed cannabis-related interests on Facebook (e.g., High Times Magazine, NORML, etc.). Samples recruited using Facebook advertising can be viewed as targeted, non-probabilistic samples (see Borodovsky et al., 2018 for an overview of this sampling method). A hyperlink embedded in the image and text of the ad directed individuals to the informed consent page hosted by a secure online data acquisition platform (Qualtrics, 2019). Individuals who reported being younger than 18 were excluded from the study. Qualtrics data quality functions prevented multiple responses from a single individual and ensured that responses came from people and not Internet bots using CAPTCHA verification. All procedures were approved by Dartmouth Colleges' Institutional Review Board.

A sample of 2593 participants consented to participate, completed the survey, and were judged to not be a robot. Participants were asked if they had ever used cannabis (no/yes) and those who reported "never" were excluded in analyses ($n = 42$). An additional five participants were excluded for not passing quality checks and one participant was excluded for reporting an age of 90 or above. The final sample was 2545 participants.

2.2. Demographic and cannabis use characteristics

See Table 1 for details of participant characteristics. The mean age of the sample was 48.35 (12.9) with a range of 18–79. The mean age of first cannabis use was 16.03 (5.2). Much of the sample was male (59.6 %), Caucasian (88.5 %), and had attended some college (60.8 %). Most of the sample was either employed full-time (42.7 %) or reported being retired or disabled (38.6 %). Over half of the sample reported smoking a tobacco cigarette in the last month (55.1 %).

2.3. Measures

2.3.1. Cannabis use—Participants indicated the number of days (0, 1–2, 3–5, 6–9, 10–19, 20–25, 26–29, All 30 days; SAMHSA, 2018) and typical times per day (1, 2–3, 4–5, 6–10, > 10) that they used cannabis in the last 30 days (Budney et al., 1999; Stephens et al., 2000, 2004). Lifetime number of methods used to administer cannabis and number of days participants smoked a tobacco cigarette in the last 30 days were also assessed.

2.3.2. Delay discounting—The DD rate (k), was obtained using a 5-trial Delay Discounting task (Koffarnus and Bickel, 2014). Participants made a series of five choices regarding whether to receive \$500 now or \$1000 after a delay. The delay for the first choice was three weeks. For each trial, the delay was adjusted based on the participant's previous choice (i.e., choosing the immediate reward shortened the delay experienced during the subsequent trial and choosing the delayed reward lengthened the delay). The combination of choices made on the five trials resulted in one of 32 possible outcomes, each of which was assigned a pre-determined k value (Koffarnus and Bickel, 2014). The raw k values were positively skewed, thus we used $\text{Ln}(k)$ values for analyses. Notably, higher DD corresponds with greater impairment.

2.3.3. Negative urgency—The Negative Urgency (NU) short version has 4 items which are rated using a four-point Likert scale (Cyders et al., 2014b). Although lower scores indicated greater agreement when the survey was administered to participants, the responses were reverse scored for analyses to indicate that greater NU scores correspond to greater NU (1= “strongly disagree” to 4= “strongly agree”). An example item from the NU short version is, “When I feel bad, I will often do things I later regret in order to make myself feel better now.” This NU short version has shown acceptable internal consistency in the past (Cyders et al., 2014c) and showed acceptable internal consistency in this study ($\alpha = .76$).

2.3.4. Cannabis coping motives—The Cannabis Coping Motives (CCM) subscale, one of the five motivations from the original MMM (Simons et al., 1998), has 4 items in which participants use a Likert scale (1= “almost never/never” to 5 = “almost always/always”) to indicate how frequently they use cannabis for the following reasons; “To forget my worries,” “Because it helps me when I feel depressed or nervous,” “To cheer me up when I am in a bad mood,” and “To forget about my problems.” The CCM subscale has shown good internal reliability ($\alpha = .80-.89$) in previous studies (Benschop et al., 2015; Chabrol et al., 2005). The internal reliability in the current study was also good ($\alpha = .81$).

2.3.5. Anxiety sensitivity index-3—The ASI-3 contains 18 items (1= “very little” to 5= “very much”) that reflect the overall fear of the consequences of anxiety, and the specific fears related to the physical, cognitive, and social consequences (Taylor et al., 2007). The internal reliability of the items was acceptable for the three subscales: physical ($\alpha = .77$), cognitive ($\alpha = .71$), and social ($\alpha = .70$). A summed score of all items for each subscale was computed (Taylor et al., 2007) instead of the global score (sum of all factors), because cognitive AS may be more closely related to cannabis use than the other subscales (Buckner et al., 2011).

2.4. Data analysis

Pearson's correlation coefficients were performed with DD, NU, CCM, and AS subscales (cognitive, physical, and social) to establish whether the anticipated relationships among the predictor variables were found prior to their simultaneous entry into the predictive model.

Frequency of days of cannabis use during the last 30 days was skewed such that over half of participants ($n = 1442$; 56.7 %) reported using cannabis all 30 days (See Table 2).

Approximately one sixth of the sample reported using between 1–9 days in the last month ($n = 343$; 13.5 %) and approximately one third of the sample used between 10–29 days in the last month ($n = 760$; 29.9 %). Frequency of times per day of cannabis use was assessed with a five options item: 1 time, 2–3 times, 4–5 times, 6–10 times, and 10 or more times (See Table 2). The median selection was 2–3 times per day. Less than one quarter of the sample used cannabis 1 time per day ($n = 433$; 17.0 %), about half used 2–3 times per day ($n = 1161$; 45.6 %), and approximately one third of the sample used 4 times per day or more ($n = 951$; 37.3%).

An exploratory LCA was used to identify potentially relevant subgroups of cannabis users based on the distribution and categorization of the frequency variables. Ordered categorical variables (past 30 days use and times per day) were used to develop the current LCA. Past 30 days use was collapsed into sub-groups of 1–9 days, 10–29 days, and all 30 days. The times per day variable was collapsed into sub-groups 1x per day, 2–3x per day, and 4+ x per day. A three-class solution provided the lowest AIC and adjusted BIC of the three models (See Table 3). Three frequency classes emerged: Low (1–9 days/month, 1 time/day; $n = 590$; 23 % of the sample), moderate (10–29 days/month, 2–3 times/day; $n = 1034$; 41 % of the sample), and high (30 days/month, 4 times/day; $n = 921$; 36 % of the sample). Individual observations were assigned to a single latent class based on the highest posterior probability of membership.

A multinomial logistic regression was performed to model the relationship between DD, NU, CCM, AS subscales (cognitive, physical, and social), and membership in frequency of use classes. Age, gender, employment, (yes vs. no) tobacco cigarette use, and number of cannabis administration methods ever used were included as covariates in the model. Model fit, goodness of fit, and the unique contributions of each overall predictor variable in the model were calculated prior to the variable estimates that separately contrasted the high frequency class from the low and moderate frequency classes.

Note that a supplemental¹ LCA and multinomial logistic regression with new frequency classes were conducted with additional parameter constraints to test the robustness of the relationship between the derived classes and the independent variables of interest (See Supplementary material). Unlike the original LCA, item response probabilities were constrained, the same multinomial logistic regression was repeated and the results were congruent with the first multinomial analysis described and reported on below. This suggests that the findings from the multinomial logistic regression were unlikely to be influenced by a lack of additional parameter constraints that were present in the initial LCA.

¹Supplementary material can be found by accessing the online version of this paper at <https://nam05.safelinks.protection.outlook.com/?url=http%3A%2F%2Fdx.doi.org&data=02%7C01%7CMichael.J.Sofis%40dartmouth.edu%7C3b5c8a1c0a9c4d7e0c3f08d6fd555d34%7C995b093648d640e5a31ebf689ec9446f%7C0%7C0%7C636974940419889276&sdata=kr9bp3S8I1JGjRGwoZDz3ygnDZbV0pRfViyha%2BC2FE%3D&reserved=0> and by entering doi: ...

3. Results

3.1. Correlations among predictor variables

DD showed a low, positive correlation with CCM ($r = .15, p < .001$) and a negative correlation with NU ($r = -.15, p < .001$) such that higher DD was related to greater CCM and NU. DD was very weakly and positively correlated with the three AS factors (r 's $< .06, p < .05$). CCM showed a moderate positive correlation with NU ($r = .31, p < .001$) such that greater CCM corresponded with greater NU. CCM showed moderate sized positive correlations with cognitive AS ($r = .32, p < .001$), physical AS ($r = .33, p < .001$), and social AS ($r = .33, p < .001$). NU also showed moderate sized positive correlations with cognitive AS ($r = .33, p < .001$), physical AS ($r = .37, p < .001$), and social AS ($r = .37, p < .001$).

3.2. Multinomial logistic regression model

The multinomial logistic regression showed that the addition of the predictors improved the fit between model and data compared to a model that only contained the intercept, $\chi^2 (26, n = 2545) = 244.7$, Nagelkerke $R^2 = .10, p < .001$. Both Pearson ($p = .43$) and deviance ($p = .07$) chi-square indicators of goodness of fit were not statistically significant, which suggests a good model fit. Significant unique contributions were made such that higher frequency of use was associated with greater DD ($\chi^2 = 6.0, p = .05$), greater CCM ($\chi^2 = 73.3, p < .001$), and lower levels of cognitive AS ($\chi^2 = 12.1, p = .002$). However, there was not an effect of NU ($\chi^2 = 2.24, p = .33$), physical AS ($\chi^2 = .60, p = .74$), or social AS ($\chi^2 = .69, p = .71$) on cannabis use class membership.

Table 4 provides the results of the frequency class comparisons. The low frequency of use class exhibited significantly lower DD than those in the high frequency class (RR = .93, 95 % CI = .87, .99, $p = .02$). This suggests that a one log unit increase (12-unit range) in DD corresponded to an eight percent increase in the odds of being in the high frequency compared to the low frequency group. No significant difference in DD was observed between the moderate and high frequency classes (RR = .97, 95 % CI = .93, 1.02, $p = .29$). For CCM, those in the high frequency of use class displayed greater CCM than those in the low (RR = .55, 95 % CI = .48, .64, $p < .001$) and moderate (RR = .85, 95 % CI = .76, .95, $p < .01$) frequency classes. The low frequency of use class exhibited significantly greater cognitive AS than the those in the high frequency class (RR = 1.08, 95 % CI = 1.03, 1.14, $p = .002$) as did those in the moderate frequency class (RR = 1.06, 95 % CI = 1.02, 1.11, $p = .005$). No significant effects were found for either comparison for NU, physical AS, and social AS.

Compared to those in the high frequency class, those who reported using only one cannabis administration method showed a 471 % increase in the odds (336 % for two methods, 266 % for three methods) of being in the low frequency class compared to those who reported using all four cannabis administration methods. Compared to those in the high frequency class, those who reported using only one cannabis administration method showed a 186 % increase in the odds (187 % for two methods, 125 % for three methods) of being in the moderate frequency class compared to those who reported using all four cannabis administration methods. Moreover, not being employed ($\chi^2 = 10.33, p = .006$) and using tobacco cigarettes

in the last month ($\chi^2 = 7.89, p = .02$) were associated with greater risk of membership in higher frequency of use classes.

4. Discussion

In this study, higher frequency cannabis use was significantly associated with greater DD, greater CCM, and lower levels of cognitive AS when controlling for age, gender, employment, tobacco cigarette use, and number of cannabis administration methods ever used. These results increase confidence in prior observations that reported both DD and CCM demonstrated direct relationships with more frequent cannabis use. Further, CCM demonstrated moderate positive correlations with all AS subfactors and NU, and DD was related to greater NU, which replicates previous findings and increases confidence that the model findings were not due to interactions between the primary variables of interest (Bravo et al., 2017; Johnson et al., 2010; Steward et al., 2017). Moreover, the current relationships observed between frequency of cannabis use and both DD and CCM are congruent with growing evidence that suggests that both constructs are associated with more frequent and problematic cannabis use (Kim-Spoon et al., 2019; Lopez-Vergara et al., 2019; Manning et al., 2019; Pearson et al., 2017).

The finding that greater DD, not NU, was associated with more frequent cannabis use along with CCM suggests that, like other substances, cannabis use is likely a product of two-systems, not a single system approach to self-regulation or self-control (Hall et al., 2018; Lopez-Vergara et al., 2019). DD is a form of self-regulation that relies on the deliberative system overriding reactive system activity (McClure et al., 2004), whereas NU is primarily driven by reactive system activity (Smith and Cyders, 2016). This suggests that if NU, and not DD, was associated with more frequent cannabis use in the present study, then evidence for an emotion regulation (e.g., bottom-up) model of cannabis use would be implicated. Future research might prioritize the identification of these types of individual differences in the degree to which these two systems impact frequent cannabis and whether such profiles differentially respond to particular intervention strategies for reducing the frequency and severity of use (Lopez-Vergara et al., 2019). Targeting DD in cannabis users may be a fruitful strategy for reducing cannabis misuse because DD is associated with a greater risk for developing a SUD and SUD severity (Bickel, 2015), it decreases with effective treatment (Koffarnus et al., 2013), and it can be effectively reduced with a growing number of interventions (Mellis et al., 2019; Rung and Madden, 2018).

Second, the use of LCA to empirically derive potentially meaningful cannabis use frequency subgroups provides a model for future studies to investigate risk factors for and consequences of cannabis use as it relates to how often one uses. Determining a clearer understanding of the relationship between frequency of use and constructs such as vulnerability to negative affect and future valuation may yield practical information for use in prevention or educational messaging. Given the high correspondence observed between more frequent use and problematic cannabis use, valid frequency measures may serve as a good proxy for or predictor of problematic cannabis use (Chen et al., 1997; Hasin et al., 2016).

When aggregating DD comparisons across frequency classes, we observed a modest sized relationship between these variables. Such findings are congruent with growing evidence suggesting that DD demonstrates a modest positive association with more frequent cannabis use (Kim-Spoon et al., 2019; VanderBroek et al., 2016). Further, a recent longitudinal study showed that greater DD was predictive of more frequent cannabis use, and to an even greater degree than were tobacco and alcohol use (Kim-Spoon et al., 2019). Prior studies also suggest that greater DD is associated with more problematic cannabis use (Aston et al., 2016; VanderBroek et al., 2016), and that among those with CUD, greater DD is associated with less treatment seeking (Heinz et al., 2013) and worse treatment outcomes (Stanger et al., 2012). Cumulatively, these findings are congruent with increased evidence of an association between frequency of cannabis use and DD that is similar in direction and size to that of other substances (Amlung et al., 2017).

Greater cognitive AS showed a weak but significant association with less frequent cannabis use, which contrasts with studies that failed to demonstrate a relation (Bonn-Miller et al., 2007; Buckner et al., 2009), or found a positive association with cannabis use (Buckner et al., 2011). The direction of this relation was unlikely due to the presence of the other variables in the multinomial model because a post-hoc test following a one-way ANOVA also showed that lower cognitive AS was associated with the more frequent cannabis use classes ($F(2, 2542) = 3.2, p = .041$). Similarly, a Spearman's rank order correlation showed that cognitive AS was negatively correlated with the number of times per day of cannabis use variable ($r = -.045, p = .023$) and number of days of use ($r = -.094, p < .001$), which reduces the likelihood that the negative direction of this relationship was due to the combining of the two frequency measures in the LCA model. Together, these findings suggest that the relationship between cannabis use and AS may be more complicated than previously thought. Note that the present study sample included a much higher percentage of higher frequency cannabis users than most prior studies that examined these relationships, which may have contributed to the different observations.

A few methodological strengths of the current study warrant mention. First, the sample size was one of the largest to date used to assess cannabis use patterns and their relation to these types of psychological constructs in current adult cannabis users ($n = 2545$). Moreover, this sample showed a wide distribution of times per day of cannabis use among the higher frequency users. These characteristics suggest the current findings may generalize well to those who demonstrate more frequent use as assessed by days of use, and also indicate the importance of assessing more granular frequency variables such as episodes of use per day. Further exploration of such molecular patterns may be particularly relevant for better understanding the development of problematic use patterns and CUD (Lopez-Vergara et al., 2019). For example, a person who uses cannabis daily but only one time each evening may differ substantially in risk for problematic use from someone who uses 5 times daily and uses soon after awakening each day.

A limitation of the current study was that the LCA did not incorporate quantity, potency, or mode of administration, which are likely relevant characteristics of cannabis use that relate to risk potential. Although other studies have incorporated such measures to derive subtypes of cannabis users (Manning et al., 2019; Pearson et al., 2017), none to our knowledge have

used an LCA approach to derive frequency of use classes. Nonetheless, future studies are needed to investigate how the inclusion of other cannabis use variables to derive subtypes of cannabis use affects relationships with individual difference risk factors. The sampling method and resulting sample in the current study could be considered a limitation. The majority of participants were Caucasian (89 %) and were recruited exclusively by using social media methods, and thus may not generalize well to other races or those who do not use social media. However, the number of participants from each U.S. state positively correlated with the state population data ($r = .79, r > .001$), which suggests that the current sample was fairly representative of actual state populations. Lastly, other forms of illicit substance use and alcohol use were not assessed in the present study, which have also been shown to relate to greater DD (Amlung et al., 2017), NU (Pang et al., 2014), and coping motives (Cooper et al., 1995). However, the fact that the present study did control for tobacco cigarette use, which is likely the substance with the strongest relationship with DD (Amlung et al., 2017), provides additional evidence supporting a direct relationship between DD and cannabis use. Future research should account for variance contributed by substance use other than cannabis and tobacco use to strengthen the generality of the current findings.

5. Conclusion

The current study sought to better understand how constructs of self-regulation and emotion regulation relate and reflect competition between deliberative and reactive systems that underlie individual differences driving cannabis use in a large sample of cannabis users recruited through social media methods. An exploratory LCA combined times per day and days of use measures to help identify subgroups of cannabis users based on frequency of use. Incorporating LCA methods in future studies may facilitate the identification of valid and reliable patterns of cannabis use that further our understanding of individual differences that increase the risk of frequent or problematic cannabis use. The present data replicate past findings that showed that using cannabis to cope with negative affect related to more frequent use and extended those findings by demonstrating that higher levels of DD, not NU, were jointly associated with more frequent cannabis use. Poor self-regulation expressed by excessive discounting of delayed rewards and maladaptive emotion regulation characterized by using cannabis to cope with negative affect may both be relevant intervention targets for treatments designed to reduce cannabis use and prevent the development of cannabis use problems.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Funding

This research was supported by NIDA grant T32DA037202, NIDA grant P30DA029926, and NIDA grant T32MH115882 which had no other role other than financial support.

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Table 1Participant Characteristics ($n = 2545$).

Age, m (SD)	48.35 (12.9)
Gender	
Male, n (%)	1517 (59.6)
Female, n (%)	1028 (40.4)
Race and Ethnicity	
Caucasian, n (%)	2252 (88.5)
African American, n (%)	32 (1.3)
Hispanic, n (%)	95 (3.7)
Native American/Alaskan Native, n (%)	64 (2.5)
Other, n (%)	102 (4.0)
Level of Education	
High school or less, n (%)	997 (39.2)
Some college, n (%)	946 (37.2)
Associates or higher, n (%)	602 (23.6)
Employment	
Full-time	921 (42.7)
Part-time	225 (10.4)
Student	29 (1.3)
Retired/Disabled	833 (38.6)
Unemployed	148 (6.9)
Used Tobacco Cigarette in Last 30 Days	
No, n (%)	1143 (44.9)
Yes, n (%)	1402 (55.1)

Participant demographic characteristics collected which included age, gender, race and ethnicity, education, employment, and tobacco cigarette use in the last 30 days.

Table 2

Cannabis Use Frequency Distributions.

	Frequency of Use	<i>n</i>	Percent (%)
How many days did you use cannabis in the past 30 days?	1–2 days	118	4.6
	3–5 days	119	4.7
	6–9 days	106	4.2
	10–19 days	231	9.1
	20–25 days	265	10.4
	26–29 days	264	10.4
	All 30 days	1442	56.7
On days of marijuana use in the past 30 days, how many times per day did you usually use?	1 time	433	17
	2–3 times	1161	45.6
	4–5 times	601	23.6
	6–10 times	245	9.6
	More than 10 times	105	4.1

Proportion of participants endorsing each sub-item for days of cannabis use (top panel) and times cannabis is used per day (bottom panel).

Table 3

Fit Statistics Latent Class Solutions –1 to 5 Classes.

Model	AIC	BIC	aBIC	# of Rho Parameters	Log-likelihood	Entropy
1-Class	544.86	568.23	555.52	4	−5039.39	1
2-Class	73.05	125.63	97.04	8	−4798.49	0.59
3-Class	28.00	109.79	65.31	12	−4770.96	0.51
4-Class	38.00	149.00	88.63	16	−4770.96	0.46
5-Class	48.00	188.21	111.95	20	−4770.96	0.37
Item-response probabilities						
Frequency of Use	Class 1		Class 2		Class 3	
1–9 days past 30 days	0.46		0.01		0	
1 time per day	0.56		0.02		0.01	
10–29 days in past 30 days	0.35		0.15		0.45	
2–3 times per day	0.37		0.21		0.87	
30/30 days	0.19		0.84		0.55	
4+ times per day	0.07		0.77		0.12	

Note. AIC = Akaike Information Criterion, BIC = Bayesian Information. aBIC = Adjusted Bayesian Information Criterion.

Top panel shows fit statistics for each of the class solutions and the bottom panel show the item-response probabilities that each sub-item was in the low (Class 1), moderate (Class 2), and high (Class 3) frequency of use classes.

Table 4

Parameter Estimates.

		B	SE	Wald	df	Sig.	RR	CI - RR	
								LB	UB
Low Use Vs. High Use	Intercept	−1.22	.527	5.32	1	.021			
	DD	−.075	.031	5.91	1	.015	.928	.874	.986
	CCM	−.599	.073	66.4	1	.000	.549	.476	.635
	NU	.124	.099	1.57	1	.210	.884	.728	1.07
	Age	.009	.005	3.14	1	.076	1.009	.999	1.02
	AS_physical	.015	.024	.372	1	.542	1.015	.968	1.06
	AS_cognitive	.080	.026	9.82	1	.002	1.084	1.031	1.14
	AS_social	−.011	.032	.119	1	.730	.989	.929	1.05
	Female	.005	.116	.002	1	.965	1.005	.801	1.26
	Work	.260	.123	4.47	1	.035	1.297	1.019	1.65
	No Tobacco Use	.068	.114	.354	1	.552	1.070	.856	1.34
	One Method	1.55	.174	79.38	1	.000	4.707	3.347	6.62
	Two Methods	1.21	.195	38.59	1	.000	3.363	2.294	4.93
	Three Methods	.977	.203	23.19	1	.000	2.657	1.785	3.96
Moderate Use Vs. High Use	Intercept	−.551	.422	1.71	1	.192			
	DD	−.026	.025	1.12	1	.291	.974	.928	1.02
	CCM	−.163	.054	9.06	1	.003	.850	.764	.945
	NU	−.012	.083	.020	1	.889	1.012	.861	1.19
	Age	.004	.004	.805	1	.370	1.004	.996	1.01
	AS_physical	−.003	.020	.018	1	.893	.997	.959	1.04
	AS_cognitive	.060	.021	7.78	1	.005	1.061	1.018	1.11
	AS_social	−.022	.027	.691	1	.406	.978	.928	1.03
	Female	.090	.096	.873	1	.350	1.094	.906	1.32
	Work	.323	.103	9.76	1	.002	1.381	1.128	1.69
	No Tobacco Use	−.205	.096	4.59	1	.032	.814	.675	.983
	One Method	.623	.122	25.88	1	.000	1.864	1.466	2.37
	Two Methods	.623	.141	19.59	1	.000	1.865	1.415	2.46
	Three Methods	.225	.150	2.26	1	.133	1.253	.934	1.68

Multinomial logistic regression results comparing low vs. high frequency and moderate versus high frequency classes for each variable. The reference category is the High Use Class. Significance values for the overall model and specific comparisons were bolded and italicized. Four methods is the referent category for methods of use.