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Heterogeneous Patterns of Marijuana Use Motives Using Latent Profile Analysis

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Abstract

Background: Given that marijuana use is often associated with detrimental physical and mental health problems, research examining motives for its use is critical for effective remedial and preventive treatment. To date, the majority of research on marijuana use motives has used variable-centered analyses, which overlooks potentially meaningful heterogeneous response patterns and the associations of those patterns with other risk/protective factors.

Methods: To address this gap, in the current study, we conducted a person-centered analysis (latent profile analysis) to identify subgroups of participants based on endorsed marijuana use motives, and examined the construct validity of the optimal class solution (covariates included sociodemographic (e.g., age), psychiatric (e.g., depression), and marijuana-use indices (e.g., use-frequency, use-related problems). Participants were 898 college students ($M_{age} = 20.93$, $SD_{age} = 3.10$; 68.9% female) who completed an anonymous online survey examining substance use and psychological well-being, were 18 years or older, and endorsed lifetime marijuana use. Data were collected November 2016 through February 2018.

Results: Results identified four unique classes of coping, conformity, social, and enhancement marijuana use motives: (a) “Low Motives” (37.6%), (b) “High Conformity” (4.9%), (c) “Low Conformity” (45.8%), and (d) “High Motives” (11.7%). In terms of covariates, higher motive classes tended to report more frequent and problematic use. The two classes uniquely characterized by conformity motives only differed on past-month marijuana use frequency.

Conclusions/Importance: The current findings provide evidence that specific classes of motives were not only associated with marijuana use frequency and problems but other risk and protective factors, such as anxiety sensitivity and social support.

Keywords

Marijuana motives; latent profile analysis; person-centered

Introduction

Marijuana is one of the most commonly used psychoactive substances in the United States, and with more states legalizing medical and recreational use, rates are predicted to increase, particularly among college students (Palamar, Ompad, & Petkova, 2014; Schulenberg et al., 2017). While data indicate that most college students who use during this period will not go on to develop a substance use disorder (e.g., Borsari & Carey, 2001), many students view substance use as simply part of the “college experience.” Given the potential for negative consequences (e.g., decreased school/work performance; increased arguments with family/friends), understanding the reasons students are using marijuana remains important. Indeed, a large body of work has found that substance use motives serve as the “final pathway” to substance use (e.g., see Cooper, Kuntsche, Levitt, Barber, & Wolf, 2016 or Kuntsche, Knibbe, Gmel, & Engels, 2005 for reviews).

Motivational model of marijuana use

Building on Cox and Klinger’s (1988) motivational model of alcohol use, Cooper (1994) posited that drinking behaviors are motivated by different outcomes that can be classified along two dimensions: *valence* (positive or negative reinforcement) and *source* (internal or external). Cooper (1994) crossed these two dimensions to identify four drinking motives: *coping* (e.g., to alleviate negative internal consequences), *conformity* (e.g., to avoid negative external/social consequences), *social* (e.g., to obtain positive external/social rewards), and *enhancement* (e.g., to obtain positive internal rewards). Simons, Correia, Carey, and Borsari, (1998) adapted Cooper’s drinking motives measure to examine marijuana use. Since then, research has progressed to support that, like alcohol use, marijuana use motives are associated with distinct marijuana use behaviors. In a recent review of alcohol, marijuana, and tobacco use motives for example, Cooper et al. (2016) note that coping and enhancement motives are both associated with more frequent marijuana use, as well as problems related to use, though the strength and reliability of the association is less stable for enhancement motives. In contrast, social motives are only associated with marijuana use frequency at the zero-order level when other motives are not controlled for, while conformity motives are either unrelated or negatively related to use frequency.

Marijuana motives and person-centered analysis

To date, the majority of the motives research has used variable-centered analysis (e.g., linear/multiple regression), which examine relationships among variables (e.g., to predict outcomes; Muthén & Muthén, 2000). This is a concerning limitation of the literature given the high correlations often found across substance use motives, including marijuana (Kuntsche et al., 2005; Simons et al., 1998), which are typically handled by examining motives in isolation (e.g., Bonn-Miller, Vujanovic, & Zvolensky, 2008) or by statistically controlling for other motives (e.g., Cloutier, Blumenthal, & Mischel, 2016; Semcho, Bilsky, Lewis, & Leen-Feldner, 2016). However, these approaches assume that participants have been sampled from a single population (Collins & Lanza, 2010), ignoring unobserved heterogeneity that may exist within populations, and therefore cannot examine how the heterogeneity in marijuana motive profiles may differentially relate to distinct marijuana-related outcomes.

In contrast, person-centered analyses examine relationships between individuals (Muthén & Muthén, 2000). Person-centered analyses assume heterogeneity within the sampled population and that meaningful subpopulations/subgroups of individuals can be identified by shared attributes (Muthén & Muthén, 2000). Latent profile analyses (LPA), a type of person-centered approach, uses observed continuous data to assign class memberships (Goodman, 1974). Rather than focusing on a single motive, or removing the shared variance between motives, LPA uses the entire pattern of co-occurring responses to categorize subgroups of individuals. Altogether, person-centered approaches like LPA provide a more robust and comprehensive approach to distinguish the outcomes and characteristics of marijuana use motives. Identifying meaningful subgroups of marijuana users based on their patterns of motives allows researchers and clinicians to address common risk/protective factors and mental health needs/outcomes for each subgroup as well as investigate etiological factors to distinguish subgroups from each other.

Despite the importance of person-centered approaches, only a handful of studies have used them to identify subgroups of marijuana users (e.g., Pearson, Bravo, & Conner, 2017). These studies have predominately used marijuana use frequency and problems to define their subgroups (e.g., Pearson et al., 2017). No studies to date have examined subgroups of marijuana users defined by their specific motive patterns. In contrast, person-centered approaches have been conducted to examine subgroups of alcohol users based on their alcohol use motives (e.g., Cadigan, Martens, & Herman, 2015; Stapinski et al., 2016). For example, one study of undergraduate drinking motives found a six-class solution wherein classes with high coping and positive reinforcement (enhancement and social) motives endorsed the most alcohol related problems, while those with higher coping motives and either high or low positive reinforcing motives reported the highest depression severity (Cadigan et al., 2015). Another study found a four-profile solution in which older adolescents with anxiety or depressive disorders were six times more likely to fall into the high-risk motives drinking class characterized by high coping motives (Stapinski et al., 2016). Collectively, the extant literature supports the empirical identification of alcohol users who endorse similar patterns of use motives, and such identification has helped explain the etiology of alcohol use. A clear next step is to consider whether similar patterns can be identified for marijuana use motives.

A second existing limitation of the marijuana use motives literature is that no studies, to the authors' knowledge, have included other individual-level risk factors (e.g., depression; anxiety sensitivity [AS]) to distinguish identified subgroups of participants. In addition to marijuana use experiences (e.g., marijuana use frequency, age of first use, co-administration with other substances), extant work indicates that motives for marijuana use may be influenced by other sociodemographic and psychiatric characteristics. Indeed, studies have reported positive associations among transdiagnostic risk factors for marijuana use motives, such as age, depression, and AS (Bonn-Miller, Zvolensky, Bernstein, & Stickle, 2008; Cooper et al., 2016; Zvolensky et al., 2007; Zvolensky et al., 2009). For example, Zvolensky et al. (2009) reported unique relations between AS and coping motives as well as conformity motives among a marijuana-using sample of young adults, even after accounting for marijuana use, cigarette use, negative affectivity, and other marijuana use motives. Further, perceived social support from friends and/or family may serve as protective factors for

riskier marijuana use motives (e.g., coping, enhancement) and antecedents for less problematic motives (e.g., social), as both positive and negative associations have been observed between perceived peer and parent social support with marijuana use frequency (Piko, 2000; Marshal & Chassin, 2000).

The current study

The aim of the current study was to use a person-centered statistical approach to identify the number, nature, and construct validity of marijuana use motive classes. We further examined which, and to what extent, sociodemographic (e.g., age), psychiatric (e.g., depression, AS), marijuana-use indices (e.g., past month use frequency, co-administration of marijuana with other substances), and perceived social support from family and friends would be differentially associated with the classes obtained from the optimal class solution. Given the lack of extant literature in this area, we did not generate specific a priori hypotheses regarding the number and nature of classes. To ensure we obtained adequate variability in responses, and consistent with prior work we focused on participants reporting any lifetime marijuana use (e.g., Buckner, Bonn-Miller, Zvolensky, & Schmidt, 2007; Simons & Carey, 2002; Hecimovic, Barrett, Darredeau, & Stewart, 2014).

Method

Participants and procedure

The final sample comprised 898 college students ranging in age from 18 to 45 years ($M_{age} = 20.93$, $SD_{age} 3.10$; 68.9% female) drawn from a larger, anonymous online survey study ($N = 1918$) focused on polysubstance use and psychological well-being. Participants were recruited from a general undergraduate subject pool (49.2% psychology majors) at a large university in Texas, in which marijuana use is illegal for medical and recreational purposes (with the exception of low-tetrahydrocannabinol cannabidiol for patients with intractable epilepsy). Data were collected every semester from November 2016 through February 2018. Participants were included in the final sample if they met the following eligibility criteria: (1) age 18 years or older, (2) reported use of marijuana at least once in their lifetime, and (3) ability and willingness to provide informed consent for study participation. All procedures were approved by the University of North Texas Institutional Review Board prior to participant contact. See Table 1 for additional detailed descriptions (e.g., race/ethnicity) of the full sample and individual classes.

Measures

Marijuana use motives—The *Marijuana Motives Measure* (MMM; Simons et al., 1998) includes 25 self-report items adapted from the Drinking Motives Questionnaire-Revised (Cooper, 1994) to quantify levels of five motive categories with regard to marijuana use: coping (e.g., “to forget my worries”), conformity (e.g., “so you won’t feel left out”), social (e.g., “to enjoy a party”), enhancement (e.g., “because it makes me feel good”), and expansion (e.g., “to expand my awareness”). Each subscale includes the sum of five items, rated on a scale of 1 (*almost never/never*) to 5 (*almost always/always*), indicating how often participants use marijuana for the listed reason. Total subscale scores range from 5 to 25, with higher scores indicating a greater frequency of given marijuana use motive. These

measures evidence good psychometric properties among young adult samples, including internal consistency (e.g., current sample: all α 's > .913), factorial validity, and criterion-related validity in predicting use problems (Simons et al., 1998; Simons, Correia, & Carey, 2000). Of note, the administration of the expansion motives subscale occurred later in the course of data collection resulting in a significant amount of missingness on this subscale only. For this reason and in an attempt to facilitate direct comparisons across substances (cf. Comeau, Stewart, & Loba, 2001), only coping, conformity, social, and enhancement motives were examined in the current study. Ultimately, the total scores from these four marijuana motives subscales served as the four continuous indicators in the LPA analysis.

Covariates: Given theoretical and empirical overlap with marijuana use motives, age, depression, AS, social support, marijuana problems, age of first marijuana use, past month marijuana frequency, and lifetime co-administration of marijuana with other substance were selected as covariates.

Age.: For age, participants selected from a drop-down menu their age in years in response to “How old are you?”

Depression.: Participants completed the *Patient Health Questionnaire* (PHQ-9; Löwe, Kroenke, Herzog, & Gräfe, 2004). The PHQ-9 is a nine-item scale that asks participants about the frequency of which they experience various depression symptoms within the preceding two weeks. Specifically, participants rate on a 0 (“not at all”) to 3 (“nearly every day”) scale the extent to which they have been bothered by depression symptoms within the past two weeks (e.g., “feeling down, depressed, or hopeless”). Responses from each item are summed with higher values reflecting more depression symptoms. The PHQ-9 evidences good psychometric properties among young adult samples, including internal consistency (e.g., current sample: α = .912) and criterion-related validity in predicting depressive disorder diagnoses on clinical interviews (e.g., SCID; Löwe et al., 2004).

Anxiety sensitivity.: Participants completed the *Anxiety Sensitivity Index-3* (ASI-3; Taylor et al., 2007). The ASI-3 is an 18-item measure comprised of three, six-item subscales: Physical (e.g., “when I feel pain in my chest, I worry that I’m going to have a heart attack”), Cognitive (e.g., “when I cannot keep my thoughts seem to speed up, I worry that I might be going crazy”), and Social (e.g., “I worry that other people will notice my anxiety”) Concerns. Participants rated the degree to which they agreed with sentences that focused on certain negative consequences of anxiety symptoms by selecting from a 5-point Likert scale, ranging from 0 (“very little”) to 4 (“very much”). Each subscale item is summed, with higher values reflecting more severe AS symptoms. The subscales from the ASI-3 evidence good psychometric properties among young adult samples, including internal consistency (e.g., current sample: all α 's > .861), factorial validity, and criterion-related validity in predicting relevant anxiety disorders (e.g., Panic, Social Anxiety; Taylor et al., 2007). All three ASI-3 subscales were included as covariates in the secondary analyses.

Perceived social support.: Participants completed the *Multidimensional Scale of Perceived Social Support* (MSPSS; Zimet, Dahlem, Zimet, & Farley, 1988). The MSPSS is a self-report measure used to assess perceived social support from friends, family, and a special

person (e.g., “I can talk about my problems with my friends”; “I get the emotional help and support I need from my family”). Participants were asked to indicate their level of agreement with each statement based on 7-point Likert scale (1 = *Very strongly disagree*, 7 = *Very strongly agree*). Total subscale scores were summed all items on the subscale; higher scores indicated greater perceived social support. The subscales from the MSPSS evidence good psychometric properties among young adult samples, including internal consistency (e.g., current sample: all α 's > .931) and factorial validity (e.g., Dahlem, Zimet, & Walker, 1991; Zimet, Powell, Farley, Werkman, & Berkoff, 1990). To minimize the number of covariates tested, in the current study only perceived social support from friends and family were examined.

Marijuana use problems. Participants completed the *Marijuana Problems Index* (MPI; Johnson & White, 1995; Knapp et al., 2018; Simons & Carey, 2002); a modified version of the Rutgers Alcohol Problems Index (White & Labouvie, 1989). The MPI is a 23-item scale that assess how often users encountered various problems associated with marijuana in the past year (e.g., “Had a fight, argument, or bad feelings with a friend”) on a scale of 1 (“Never”) to 5 (“More than 10 times”). All items are summed to create a total MPI score, with higher scores indicating more marijuana use problems. The MPI evidences good psychometric properties among young adult samples, including internal consistency (e.g., current sample: α = .958). The total sum score for the MPI was included as a covariate in the secondary analyses.

Marijuana use experience indices. A three-item self-report measure based on a structured interview detailed in Barrett, Darredeau, and Pihl (2006) was used to assess marijuana use experience indices. More specifically, these questions asked about age at first use, past-month use frequency, and lifetime marijuana use co-administration with other substances.

Age at first use. Participants were asked a single-item, face-valid question, “*What was the age at which you first tried cannabis/marijuana?*” with responses ranging from 10 to 28 years. Age at first marijuana use was included as a continuous variable in the secondary analyses.

Past-month marijuana use frequency. Participants were asked a single, face-valid question regarding past month marijuana use frequency (“*In the last 30 days, how many times have you used cannabis/marijuana?*”) with responses ranging on a seven-point, Likert-type scale: 1 (“None”), 2 (“1–2”), 3 (“2–3”), 4 (“4–5”), 5 (“6–9”), 6 (“10–19”), and 7 (“20+”). The wording of this item and associated responses are similar to those used in the Monitoring the Future Survey (Bachman, Johnston, & O’Malley, 2014), which is regularly administered to nationally representative samples of young adults; this item also has been used in similar studies assessing college student substance use (e.g., Barrett et al., 2006; Kearns et al., 2018). Past-month marijuana use frequency was included as a continuous variable in the secondary analyses.

Lifetime marijuana co-administration. Participants were asked a single-item, face-valid question, “*In your lifetime, have you ever co-administered cannabis/marijuana with any*

other substance?” in which participants could respond “Yes” or “No.” Lifetime marijuana co-administration was included as a dichotomous variable in the secondary analyses.

Data analytic plan

Latent profile analysis—For the primary analyses, LPA was conducted to categorize participants into latent subgroups based on participant endorsement of four marijuana use motives: social, coping, enhancement, and conformity. Each of the marijuana use motive subscales were modeled as continuous indicators. Missing data were minimal (i.e., <1% on any given item). Maximum Likelihood estimation with robust standard errors as the estimator was used to address non-normality and estimate missing data in Mplus 8. For the LPA, we used the “lrtstarts” option; the number of initial and final iterations for the *K-1* class model was 20 each, and the number of initial and final iterations for the *K* class model was 50 and 20, respectively. The general practice of LPA is to test the fit of a two-class model and systematically increase the number of classes until adding more classes is no longer warranted or meaningful. Following standard recommendations, both statistical and nonstatistical criteria were evaluated to determine the optimal latent class model (DiStefano & Kamphaus, 2006; Marsh, Lüdtke, Trautwein, & Morin, 2009; Nylund, Bellmore, Nishina, & Graham, 2007). For statistical criteria, three estimators of the relative quality of statistical models for a given set of data were evaluated for model selection: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample-size adjusted BIC (SSABIC) values. With these criteria, lower values indicate better model fit. Furthermore, adjusted Lo–Mendell–Rubin (LMR) Likelihood Ratio Test and Bootstrapped Likelihood Ratio Test (BLRT) values were evaluated for each model to compare the improvement in fit. For these criteria, statistically nonsignificant finding for the *K-1* class indicates a better fit for the *K* class solution (Nylund et al., 2007). Finally, entropy values were examined for each model. Entropy values provide an indication of the classification accuracy, with values ranging between 0 and 1—values near 1 indicating better model fit. Regarding nonstatistical criteria, considerations were made for parsimony, interpretability, and size of latent classes (e.g., <10%) associated within each model (Hipp & Bauer, 2006; Lanza & Rhoades, 2013). Notably, excluding small class sizes that are more prone to be spurious is generally recommended as it helps improve the overall accuracy and stability of the findings (e.g., Hipp & Bauer, 2006). Overall, model selection was based equally on (1) goodness-of-fit statistics, (2) parsimony, and (3) conceptual and practical interpretability.

Characterization of classes—With the aim of objectively categorizing/defining subgroups and consistent with prior work (e.g., Contractor, Caldas, Weiss, & Armour, 2018; Müllerová, Hansen, Contractor, Elhai, & Armour, 2016), the most likely class membership—based on posterior probabilities indicating LPA group classification—were imported into SPSS 24.0 and univariate analyses of variance (ANOVA) were conducted to examine omnibus differences on marijuana use motives between LPA classes; follow-up pairwise Games-Howell *post hoc* analyses were used to evaluate specific between-class differences in marijuana use motives and Cohen’s *d* were interpreted for effect size estimates.

Association between covariates and class membership—The three-step approach was used to evaluate the construct validity of the optimal class solution. Broadly, the three-

step approach estimates the best class solution (Step 1), creates a variable for each case specifying the class for which they most likely belong based on Step 1 posterior probabilities (Step 2), and fits an auxiliary model for each class where all of the distal/predictor auxiliary variables (i.e., covariates) are used to predict class membership in one multinomial logistic regression model that accounts for misspecification bias (Step 3; Asparouhov & Muthén, 2014; Kamata, Kara, Patarapichayatham, & Lan, 2018; Vermunt, 2010). While a single variable for the most likely class membership was created in Step 2, the classification uncertainty information was retained and evaluated as measurement errors of classification in the form of a $k \times k$ matrix, where k is the class number (see Kamata et al., 2018). In Step 3, all covariates are evaluated in the model simultaneously. For the current study, the three-step approach examined which theoretically derived demographic (i.e. age), psychiatric (e.g., AS, depression), and marijuana-related covariates impacted likelihood of *specific* group classification (e.g., between Classes 1 versus 2). Adjusted Odds Ratios (*OR*) and 95% confidence intervals were interpreted for effect size estimates. The three-step approach was conducted in Mplus using the “AUXILIARY are (R3STEP)” command. The default for a three-step approach in Mplus is to use listwise deletion; hence, the sample size for the secondary analyses included 771 participants.

Results

Latent profile analysis

Table 2 provides the results of LPA fit indices for all examined models. There were model convergence problems with the seven-class solution; as such, only the first six models were compared to determine the optimal model, and $-10,598.463$ was the best likelihood value retained for final optimization (replicated two times). Of the remaining solutions, all models indicated significant LMR and BLRT values, suggesting that each subsequent class solution was a better fit than the former. This trend was sustained for the AIC, BIC, and SSABIC values, indicating that the six-class solution would be the best fitting model—however, notably, there is a substantive drop-off in BIC and SSABIC values reduction in each model after the three-class solution. Additionally, the four-class solution evidenced the highest entropy value, indicating marked model fit improvement over the two- and three-class models, and slight improvement over the five- and six-class models. Regarding nonstatistical criteria, the four-class model was more parsimonious than the five- or six-class solutions. Furthermore, both the five- and six-class models produced subgroups composed of less than 10% of the overall sample and added little interpretable value to the model (e.g., a moderate social/coping/enhancement and low conformity group). Coupling results of the statistical (i.e., fit indices) and nonstatistical criteria (i.e., parsimony and greater practical interpretability), the four-class model was selected as the optimal model. Notably, this four-class model appeared to correctly classify between 94.1% and 95.8% of individuals into their most likely latent profile category, with 0.0%–3.3% of individuals being misclassified on any given class. (See Table 3 for detailed results from the classification accuracy matrix.) Figure 1 provides a graphical depiction of the four-class model.

Characterization of classes

Results of the omnibus ANOVA and *post hoc* analyses indicated significant between-class differences across all four marijuana motives subscales ($p < .001$). As seen in Table 4, all of the four one-way ANOVAs (where the class membership was the independent variable, and each of the four marijuana motives subscale was the dependent variable in each independent model) were statistically significant and had large effect sizes (partial $\eta^2 = .55$ to $.78$; Cohen, 1969; Richardson, 2011). This suggests that a variation in class membership accounted for a large proportion of the total variability in the marijuana motive subscale score tested in each independent model. Furthermore, all statistically significant pairwise differences between classes indicated medium to large effect sizes ($d = 0.56$ to 4.46). Generally, Class 1 reported the lowest scores across all the marijuana motive subscales, whereas Class 4 reported the highest scores across all the marijuana motive subscales. As such, Class 1 (37.6% of sample) was labeled *Low Motives*, and Class 4 (11.7% of sample) was labeled *High Motives*. Alternatively, Class 2 (4.9% of sample) reported relatively low social, coping, and enhancement motive scores but high conformity motive scores. Given this trend, Class 2 was labeled *High Conformity*. Finally, Class 3 (45.8% of sample) reported relatively high social, coping, and enhancement motive scores but low conformity motive scores. As such, Class 3 was labeled *Low Conformity*. See Table 4 for the number of cases in each class and full descriptions for the class comparison analyses (e.g., means, omnibus, and pairwise effect sizes).

Association between covariates and class membership

High conformity—Generally, the *High Conformity* class (i.e., Class 2) was associated with past-month marijuana use frequency; more specifically, the increased frequency of use decreased the odds of being in the *High Conformity* class relative to all other classes ($p's < .001$).

Low conformity

Conversely, the *Low Conformity* class (i.e., Class 3) was associated with several demographic and psychiatric characteristics, in addition to marijuana-related indices. More specifically, relative to the *Low Motives* class, increases in AS-social symptoms and social support from friends increased the likelihood of being in the *Low Conformity* class, whereas older age was associated with decreased likelihood of being in the *Low Conformity* class. Alternatively, higher AS-physical symptoms increased the likelihood of being in the *High Motives* class (i.e., Class 4), relative to the *Low Conformity* class.

Parallel/symmetrical classes—Regarding the two low and high marijuana motives classes, the only statistically significant association among our theoretical covariates and class membership likelihood was marijuana use problems; more specifically, increases in marijuana use problems increased odds of being the *High Motives* class, relative to the *Low Motives* class.

Regarding the two classes uniquely characterized by conformity motives, the only statistically significant covariate was past-month marijuana use frequency. As previously noted, increases in marijuana use frequency increased the likelihood of being in the *Low*

Conformity class, relative to the *High Conformity* class. See Table 5 for complete results of the associations between covariates and classes.

Discussion

The goal of this study was to identify groups of college students who use marijuana for similar reasons. Although previous studies have established the utility of *drinking motives* profiles among college attending adults (e.g., Cadigan et al., 2015), no study has conducted a similar examination regarding marijuana. Furthermore, among studies that have used person-centered approaches to look at marijuana use trajectories, none have examined a broad range of theoretical risk factors. To address these gaps, we used LPA to identify unique classes of marijuana use motive patterns. First, our results identified four unique profiles of coping, conformity, social, and enhancement motives: (a) *Low Motives*, (b) *High Conformity*, (c) *Low Conformity*, and (d) *High Motives*. Second, we explored how these classes of motives differed in terms of age, depression, AS, social support, marijuana problems, age of first marijuana use, past month marijuana frequency, and lifetime co-administration of marijuana with another substance. Results provide partial support for construct validity of the classes, with the covariate past month marijuana use frequency providing the most information for identifying unique classes.

Unlike the alcohol literature (e.g., Cadigan et al., 2015; Patrick & Maggs, 2010), a large percentage of marijuana users (37.6%) were represented by low (cf. moderate) marijuana use motives scores across the board. This *Low Motives* class also was generally defined by fewer problems related to marijuana use and less frequent marijuana use than each of the other classes. College students within this class are likely infrequent marijuana users who would not have developed specific motivations for use, nor have used frequently enough to experience any significant problems. Furthermore, compared to the *Low Motives* class, the *Low Conformity* class was slightly younger, reported higher AS-social concerns, and greater perceived social support from friends (but not family). One explanation for this finding could be that young adults evidencing elevated AS-social concerns may use their friendships to help regulate their high AS-social symptoms (i.e., to attenuate concerns of negative external evaluation of anxiety symptoms) and thus may not use marijuana for these purposes; however, our results suggest they may use cannabis to enrich their experiences with friends, both internally (enhancement) and externally (social), and also to attenuate negative emotions and sensations (coping). Unfortunately, there wasn't a clear/consistent pattern of both protective factors (i.e., family and friend social support) differentiating the *Low Motives* class from the other classes in terms of greater class membership likelihoods. Nevertheless, that the majority of our sample was represented by this class is likely related to our broader inclusion criteria of any *lifetime* marijuana use (cf. past year or past 30-day use) and suggests that experimental users (e.g., only tried once or twice in lifetime) can be effectively distinguished from regular users on their motive profiles. Future researchers can use this broader criterion to identify factors that prevent students who experiment with marijuana from internalizing use motives and ultimately, from transitioning into heavier/more problematic use patterns. Important next steps are to explore other potential protective factors that may better differentiate groups, such as protective behavioral strategies (e.g., setting consumption limits; Pedersen, Hummer, Rinker, Traylor, & Neighbors, 2016), or

even more complex relationships that evaluate the effect of both risk and protective factors on marijuana-related outcomes (e.g., multiple mediation models; Bravo, Prince, Pearson, & the Marijuana Outcomes Study Team, 2017).

One unique finding was an emergence of two classes differentiated by low and high conformity motives. Specifically, more frequent past month marijuana use *increased* the likelihood of being in the *Low Motives* class compared to the *High Conformity* class. In contrast, the *Low Conformity* class endorsed more frequent marijuana use than each of the other classes but fewer marijuana related problems than the *High Motives* class. Across the literature examining alcohol use motives, both age and frequency of use positively relate to endorsement of coping, social, and enhancement motives for consumption, whereas links to conformity motives typically are nonsignificant or negative (e.g., Kuntsche et al., 2014). Consistent with this literature, the current data indicate that the increased marijuana use frequency is associated with greater coping, social, and enhancement motives, as well as a decreased likelihood of use for conformity motives. This finding is also consistent with Cooper's (1994) initial interpretation of conformity motives as being more predominant in earlier substance use. However, the fact that the *Low Conformity* class was younger than the *Low Motives* class reinforces the point that age alone is an imperfect marker of where a person is at in terms of their substance using trajectory. On the one hand, this finding highlights the need for interventions among more experienced users to target coping, social, and enhancement motives as this represented the largest class (45.8%). On the other hand, the findings also highlight that there is a small percentage (4.5%) of individuals who use primarily for conformity reasons—a group characterized by less frequent marijuana use, relative to the other classes.

Of note, only some of the selected demographic, risk, and protective factors were associated with class distinctions. For example, past month marijuana use frequency distinguished between nearly all of the classes—with the *High Conformity* class endorsing the lowest frequency and the *Low Conformity* class endorsing the highest frequency. Collectively, it appears as if classes defined by high conformity endorse less frequent marijuana use overall, which is consistent with a vast body of variable-centered research in this area (see Cooper et al., 2016 or Kuntsche et al., 2005 for reviews). In contrast, age of first marijuana use was not associated with any one class membership over another. Prior work has suggested that individuals who begin using earlier in life are more prone to using marijuana for a greater range of marijuana motives as they accumulate use experiences across contexts (Cooper et al., 2016). The current data do not support this perspective; however, it is possible that the inclusion of lifetime marijuana users (including those who may have used marijuana early in life, but have since quit) has minimized the effect of age of marijuana onset. Future studies with recent or regular marijuana users (e.g., within the past 30 days) may observe different findings.

Next, young adults in the *High Motives* class reported greater AS-physical symptoms than young adults in the *Low Conformity* class. Our findings related to AS may suggest that evidencing elevated levels of AS-physical concerns (or AS-social concerns as discussed above) could increase the likelihood of developing and internalizing more marijuana use motives overall, or vice versa (increased motives for marijuana use may increase risk for

development of AS symptoms). However, AS-cognitive concerns were not associated with class membership. Future work is needed to replicate the current findings, and to prospectively investigate the longitudinal trends of marijuana use motives and the vulnerability factor of AS. Unexpectedly, depression was also not significantly associated with any class membership. This is inconsistent with studies highlighting the role of depression as an antecedent risk factor for developing riskier marijuana motives (e.g., coping) and therefore use related problems (Johnson, Bonn-Miller, Leyro, & Zvolensky, 2009). Importantly, these studies primarily investigated associations between depression and *specific* motives, whereas the current study examined associations between depression and *patterns* of motives (i.e., class membership). Additional research is needed to confirm the extent to which depression is associated with specific motives and use patterns.

The current study should be considered in light of several limitations. First, as a cross-sectional survey we cannot make causal inferences regarding the associations between motives and the selected covariates. Future studies will need to incorporate longitudinal and experimental designs to determine the temporal sequencing and causal foundations of these associations. Second, given the nature of the current sample (i.e., drawn from a psychology department pool in a state where marijuana is not legal), it will be critically important to replicate these findings in similar samples (e.g., in other nonlegalized states) as well as among college students from states where marijuana has been decriminalized/legalized. Third, while the primary focus of this study was to identify different subclasses for marijuana motives among a college student population, there remains a need to replicate and extend these findings to other developmentally and contextually distinct populations (e.g., adolescents; clinical populations; noncollege attending emerging adults; White, Labouvie, & Papadaratsakis, 2005) as well as consider additional marijuana use motives (e.g., expansion; Simons et al., 1998; Lee, Neighbors, Hendershot, & Grossbard, 2009). Fourth, one limitation of person-centered approaches, including LPA, is the significant correlations among indicators; future research may benefit from using approaches that *integrate* person and variable-centered methods (Lee & Lee, 2018). Fifth, because this was an online administered survey and individuals often struggle to recall the absolute frequency of uses (e.g., Leigh, Gillmore, & Morrison, 1998; Lintonen, Ahlström, & Metso, 2004; Schwarz, 2007), participants were asked to select a categorical range of use occasions over the past 30 days to minimize missing/unusable data. Likewise, participants were only asked a single yes/no question about co-administering marijuana with any other substances without specifying the other substance or timeframe of administration (e.g., distinguishing between concurrent versus simultaneous co-administration; Midanik, Tam, & Weisner, 2007). While these approaches are consistent with prior work, future studies should consider collecting more detailed assessments of use history and patterns with assessments that are designed to facilitate memory recall and formats that allow for more nuanced question probes to address timing and patterns of polysubstance use (e.g., Timeline Followback Interviews; Sobell & Sobell, 1992; Sobell & Sobell, 1996). Finally, the current study only considered a handful of theoretically related variables. While the classes differed on many of the selected variables at the descriptive level (see Table 1), in the final models with all of the variables entered simultaneously, classes that should have differed on more variables (e.g., *Low Motives* and *High Motives*) were statistically similar. In addition to collecting larger samples, future work

should consider other important risk factors, such as social anxiety (Cloutier et al., 2016), distress tolerance (Semcho et al., 2016), trauma exposure/post-traumatic symptom severity (Bonn-Miller, Vujanovic, Feldner, Bernstein, & Zvolensky, 2007), and externalizing symptoms (Hussong, Ennett, Cox, & Haroon, 2017) as well as protective factors, such as protective behavioral strategies (Pederson et al., 2016) and healthy emotional self-regulation (Dvorak & Day, 2014).

Implications and conclusion

Information regarding the heterogeneous patterns of marijuana use motives provides a snapshot of co-occurring marijuana use consequences as well as risk and protective factors that can be used to inform prevention and treatment efforts. The current study used a person-centered approach to identify specific marijuana motive profiles that were not only associated with marijuana frequency and problems but other theoretically relevant risk and protective factors such as AS and social support. Unlike studies using variable-centered analyses, which look at each motive and associated variables separately, this study identified common, heterogeneous motive profiles that can be used to more efficiently create tailored intervention efforts (Banes, Stephens, Blevins, Walker, & Roffman, 2014). For example, those in the *High Motives* profile experienced more marijuana problems and cognitive AS symptoms but used marijuana less often than those in the *Low Conformity* class. This suggests that focusing on reducing or modifying all four motives (including conformity) and AS-cognitive concern symptoms may reduce marijuana problems and potentially lower the likelihood of cannabis use disorder onset or severity. In contrast, those in the *Low Conformity* class were younger, used more frequently, had higher AS-social concern symptoms, and had greater social support from friends than those in the *Low Motives* class. These findings suggest that the social support of friends may be counteracting the effects of use frequency on current problems. Thus, incorporating the existing social network into preventive interventions may help prevent the development of problems while simultaneously working to reduce use frequency through reducing coping, social, and enhancement motives (e.g., replacing coping-motivated use with more positive coping strategies). As for treatment implications, considering the number and types of motives during clinical assessment is important for clinicians given this meaningful heterogeneity found among marijuana users. Nevertheless, additional research is needed to replicate and extend these patterns to different populations (e.g., adolescent, clinical, racially and ethnically diverse populations) as well as test the utility of motive profiles within an intervention context.

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Figure 1.

Latent profile of participants based on marijuana use motives. Note: The indicators are four marijuana use motives (MMM).

Table 1.

Demographics and class comparisons for full sample and four classes.^a

Variable	Full sample (N = 898)	Class 1: Low motives (n = 338)	Class 2: High conformity (n = 44)	Class 3: Low conformity (n = 411)	Class 4: High motives (n = 105)
Age <i>M</i> (<i>SD</i>)	20.93 (3.10)	20.35 (2.43)	22.20 (4.27)	20.54 (3.05)	20.74 (3.35)
Biological sex (female) <i>n</i> (%)	619 (68.9%)	230 (68.0%)	33 (75.0%)	289 (70.3%)	67 (63.8%)
Race/ethnicity <i>n</i> (%)					
Asian	45 (5.0%)	15 (4.4%)	5 (11.4%)	18 (4.4%)	7 (6.7%)
African American	118 (13.1%)	41 (12.1%)	4 (9.1%)	54 (13.1%)	19 (18.1%)
White/Caucasian	437 (48.7%)	168 (49.7%)	27 (61.4%)	193 (47.0%)	49 (46.7%)
Hispanic/Latino	189 (21.0%)	74 (21.9%)	6 (13.6%)	88 (21.4%)	21 (20.0%)
Other	10 (1.1%)	1 (0.3%)	—	9 (1.7%)	—
Multiracial	99 (11.0%)	39 (11.5%)	2 (4.5%)	49 (11.9%)	9 (8.6%)
Socioeconomic status <i>n</i> (%)					
Less than \$25,000	119 (13.3%)	39 (11.5%)	3 (6.8%)	60 (14.6%)	17 (16.2%)
\$25,000 to \$50,000	234 (26.1%)	90 (26.6%)	12 (27.3%)	107 (26.0%)	25 (23.8%)
\$50,000 to \$75,000	192 (21.4%)	69 (20.4%)	12 (27.3%)	86 (20.9%)	25 (23.8%)
More than \$75,000	353 (39.3%)	140 (41.4%)	17 (38.6%)	158 (38.4%)	38 (36.2%)
Marijuana indices					
Problematic use (MPI) <i>M</i> (<i>SD</i>) ^b	30.91 (12.77)	25.97 (7.00)	29.68 (11.29)	32.51 (11.15)	41.06 (22.76)
Age at first use <i>M</i> (<i>SD</i>) ^c	16.82 (2.24)	17.40 (2.30)	17.09 (2.18)	16.38 (2.13)	16.59 (2.06)
Past month use frequency <i>Mdn</i> (<i>IQR</i>)	2.0 [1.0, 5.0]	1.0 [1.0, 2.0]	1.0 [1.0, 1.0]	3.0 [1.0, 7.0]	2.0 [1.0, 4.0]
Lifetime co-administration <i>n</i> (%)	520 (57.9%)	134 (39.6%)	22 (50.0%)	296 (72.0%)	68 (64.8%)

^aNote: Problematic marijuana use measure via the MPI (Simons & Carey, 2002).^bData not available for 30 participants (3.3%).^cData not available for 2 participants (0.2%).

Table 2.

Fit indices from analyses of 1–7 latent classes.^{a,b}

Model	AIC	BIC	SSABIC	Entropy	LMR (p)	BLRT (p)
1 class	23,113.29	23,151.69	23,126.28			
2 class	22,508.64	22,571.53	22,530.25	.87	1228.79 (<.001)	<.001
3 class	21,494.61	21,581.01	21,523.85	.83	387.34 (.008)	<.001
4 class	21,242.93	21,353.33	21,280.29	.92	254.21 (.004)	<.001
5 class	20,945.72	21,080.12	20,991.20	.88	298.33 (<.001)	<.001
6 class	20,768.77	20,927.18	20,822.37	.90	181.60 (.013)	<.001

^aNote: AIC, Akaike information criterion; BIC, Bayesian information criterion; SSA-BIC, sample-size adjusted BIC; LMR, Lo-Mendell-Rubin adjusted likelihood ratio test; BLRT, bootstrap likelihood ratio test.

^bThe best log-likelihood value was not replicated. The p-value may not be trustworthy due to local maxima.

Table 3.Classification uncertainty rates for the fourclass solution.^a

Most likely latent class membership	Latent class in model			
	Class 1	Class 2	Class 3	Class 4
Class 1	.958	.006	.035	.000
Class 2	.024	.951	.001	.024
Class 3	.033	.000	.949	.017
Class 4	.003	.018	.038	.941

^a *Note:* Data represent a $k \times k$ matrix of classification uncertainty rates, computed using the estimated posterior probabilities and the number of individuals assigned to each of the latent profiles.

Table 4.Results of ANOVA analyses for characterization of classes.^a

Means, standard deviations, and ANOVA comparisons						
Marijuana motives	Class 1: Low motives (<i>n</i> = 338)	Class 2: High conformity (<i>n</i> = 44)	Class 3: Low conformity (<i>n</i> = 411)	Class 4: High motives (<i>n</i> = 105)	<i>F</i>	η^2
Social	7.80 ± 3.01	10.23 ± 3.75	16.76 ± 5.18	19.52 ± 3.79	362.10	.55
Coping	7.02 ± 2.93	7.30 ± 3.67	15.13 ± 5.82	18.35 ± 4.90	264.57	.47
Enhancement	9.59 ± 3.84	8.98 ± 3.31	21.24 ± 3.06	20.53 ± 6.63	825.64	.74
Conformity	6.16 ± 1.97	19.02 ± 3.59	6.18 ± 1.92	16.99 ± 3.60	1031.881	.78
Class pairwise comparisons (Cohen's <i>d</i>)						
	1 vs. 2	1 vs. 3	1 vs. 4	2 vs. 3	2 vs. 4	3 vs. 4
Social	0.71 *	2.12 *	3.42 *	1.44 *	2.46 *	0.61 *
Coping	0.08	1.76 *	2.81 *	1.61 *	2.55 *	0.60 *
Enhancement	0.17	3.36 *	2.02 *	3.85 *	2.20 *	0.14
Conformity	4.44 *	0.01	3.73 *	4.46 *	0.56 *	3.75 *

^aNote:

* $p < .001$. Marijuana motives were assessed via the MMM (Simons, Correia, Carey, & Borsari, 1998). To aid in interpreting the classes, the high subscale values that define each class have been bolded. Omnibus test statistics are presented as omnibus *F* for marijuana motives which were all statistically significant at $p < .001$. Pairwise Games-Howell *post hoc* analyses compared marijuana motives between classes. Cohen's *d* thresholds: .20 small, .50 medium, and .80 large.

Table 5.

Results of the three-step approach for the associations between covariates and classes.^a

Variable	Class 1: Low motives				Class 2: High conformity				Class 3: Low conformity	
	vs 2		vs 3		vs 4		vs 3		vs 4	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
General covariates										
Age	0.97	(0.86–1.09)	0.94*	(0.89–0.99)	0.98	(0.90–1.07)	0.97	(0.86–1.10)	1.01	(0.88–1.16)
Depression	1.04	(0.97–1.11)	1.03	(0.99–1.08)	1.00	(0.95–1.06)	1.00	(0.93–1.06)	0.96	(0.89–1.03)
Anxiety sensitivity (physical)	0.94	(0.79–1.11)	0.98	(0.92–1.04)	1.05	(0.98–1.13)	1.04	(0.89–1.23)	1.12	(0.94–1.34)
Anxiety sensitivity (cognitive)	1.03	(0.90–1.18)	0.99	(0.92–1.06)	1.04	(0.97–1.13)	0.96	(0.84–1.09)	1.01	(0.87–1.17)
Anxiety sensitivity (social)	1.09	(0.98–1.21)	1.08**	(1.03–1.14)	1.03	(0.96–1.09)	1.00	(0.90–1.10)	0.94	(0.85–1.05)
Social support (family)	1.14	(0.82–1.59)	0.95	(0.81–1.10)	0.93	(0.75–1.17)	0.83	(0.60–1.14)	0.82	(0.57–1.17)
Social support (friend)	1.06	(0.80–1.41)	1.23**	(1.05–1.43)	1.20	(0.95–1.50)	1.16	(0.87–1.54)	1.13	(0.80–1.58)
Marijuana Covariates										
Problematic use	1.12	(0.99–1.27)	1.09	(0.97–1.23)	1.14*	(1.01–1.28)	0.98	(0.94–1.01)	1.01	(0.98–1.05)
Age at first use	0.94	(0.79–1.13)	0.92	(0.84–1.01)	0.90	(0.79–1.02)	0.98	(0.81–1.17)	0.95	(0.78–1.16)
Past month use frequency	0.44**	(0.26–0.75)	1.38***	(1.18–1.62)	1.07	(0.89–1.30)	3.15***	(1.85–5.34)	2.44***	(1.43–4.18)
Lifetime substance co-admin.	0.53	(0.22–1.28)	0.39***	(0.24–0.62)	0.52	(0.27–1.01)	0.73	(0.31–1.73)	0.98	(0.36–2.69)

Note:

* $p < .05$.** $p < .01$.*** $p < .001$.^aClass 4 is High Motives. Three-step approach data presented as an adjusted OR; all covariates were entered simultaneously for analyses.