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Complex cannabis use patterns: Associations with cannabis consequences and cannabis use disorder symptomatology☆

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HIGHLIGHTS

- Considering multiple products is important when classifying cannabis use patterns.
- Results suggest five distinct classes of cannabis users.
- Class membership predicts cannabis consequences and symptomatology.
- Frequency of use remains a strong predictor of consequences.

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ABSTRACT

Background: Historically, cannabis researchers have assumed a single mode and product of cannabis (e.g., smoking plant). However, patterns of use, products (e.g., concentrates, edibles), and modes (e.g. blunts, vaporizers) are diversifying. This study sought to: 1) classify cannabis users into groups based on their use of the full range of cannabis products, and 2) examine user group differences on demographics, cannabis consequences and cannabis use disorder (CUD) symptomatology.
Methods: In a sample of college students (data collected in Fall 2017), who used cannabis in the past year (N = 1390), latent class analysis (LCA) was used to characterize cannabis users. We then added demographic characteristics, cannabis consequences, and CUD symptomatology scores separately to LCA models to examine class differences.
Results: Five unique classes emerged: high-frequency all-product users, high-frequency plant/moderate-frequency edible and concentrate users, low-frequency plant users, moderate-frequency plant and edible users, and low-frequency edible users. Demographic characteristics, cannabis consequences, and CUD symptomatology differed across classes characterized by frequency as well as product.
Conclusions: Results reflect the increasing variety of cannabis products, modes, and use patterns among college students. In this sample, frequency of use remains a strong predictor of cannabis-related consequences, in addition to type of product. As variation in cannabis use patterns continue to evolve, it is essential for researchers to conduct comprehensive assessments.

1. Introduction

Rates of cannabis use among college students have increased in recent years, with 38.3% of college students reporting annual use in 2017. Further, rates of cannabis use disorder (CUD) are highest among this age group (18–25) (Schulenberg et al., 2018). Given recent social and legal changes in recreational cannabis use, understanding increasingly diverse patterns of use is critical. Although the most common form of cannabis remains plant-based products administered via combustible modes such as pipes, joints, bongs, and blunts (Knapp et al., 2019; Schauer, King, Bunnell, Promoff, & McAfee, 2016), additional products (e.g., high potency concentrates, edibles) and modes (e.g., dab

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rig, vaporizer) are increasingly prevalent. This diversification is particularly pronounced in states with legalized recreational cannabis use (Borodovsky, Crosier, Lee, Sargent, & Budney, 2016; Budney, Sargent, & Lee, 2015; Daniulaityte et al., 2017; MacCoun & Mello, 2015; Schauer et al., 2016).

Although plant products remain the most frequently purchased, Washington state data from 2014 to 2015 to 2015–2016 suggests that concentrate use increased 770% while purchase of edibles and plant products increased 400–488% (Carlini, Garrett, & Harwick, 2017). Concentrates are of particular interest, as they demonstrate extreme potency up to 80% THC, which results in greater intoxication (Stogner & Lee Miller, 2015) compared to traditional cannabis products. Given the historical prominence of smoking plant products, it is unsurprising that previous research has not regularly measured various cannabis modes and products comprehensively. However, concentrate users demonstrate greater adverse acute and long-term physiological, cognitive, and psychological effects (Bhattacharyya et al., 2010; D'Souza et al., 2004; Ramaekers et al., 2006; Winton-Brown et al., 2011; Zuurman, Ippel, Moin, & Van Gerven, 2008). In addition, recent data highlight differential risks across cannabis products, with frequent concentrate users reporting more symptoms of CUD compared to concentrate nonusers (Bidwell, YorkWilliams, Mueller, Bryan, & Hutchison, 2018).

Most studies attempting to classify cannabis users have focused on frequency of use in various populations, including middle school students (Reboussin, Hubbard, & Ialongo, 2007), adolescents and young adults (Ellickson, Martino, & Collins, 2004; Passarotti, Crane, Hedeker, & Mermelstein, 2015), and adults (Brook, Lee, Brown, Finch, & Brook, 2011; Juon, Fothergill, Green, Doherty, & Ensminger, 2011; Tait, Mackinnon, & Christensen, 2011; Terry-McElrath et al., 2017). Despite being informative about the association between frequency and consequences, these studies did not consider complex cannabis use patterns, particularly products (e.g., concentrates, edibles), modes (e.g., vaporizers, joints), and quantity. Indeed, risk for an individual with five episodes per day of multiple high-potency products is likely very different from someone who uses a small amount of plant once per day, despite similar daily frequency.

More recent studies have examined cannabis use patterns using indicators beyond frequency. One study of adults also examined quantity (operationalized as "joint" size) and cannabis problems as class indicators and found five unique classes that followed a stepwise increase in frequency, quantity, and problems (Manning et al., 2019). In another study examining a variety of cannabis products and risky use behaviors (i.e., driving after use), four classes emerged: light plant users unlikely to drive after use, heavy plant users likely to drive after use, plant and concentrate users likely to drive after use, and light plant and edible users unlikely to drive after use (Krauss, Rajbhandari, Sowles, Spitznagel, & Cavazos-Rehg, 2017). Another study of college students used latent profile analysis to examine classes of cannabis users that also found four classes representing stepwise increasing frequency and number of consequences (Pearson, Bravo, & Conner, 2017). However, research has yet to fully classify complex patterns of cannabis use, including frequency and quantity as well as novel salient indicators such as product and mode.

No studies have examined modes of administration in addition to frequency, quantity, and products to classify cannabis users. Further, previous studies that classified patterns of use also included consequences as latent class indicators. As cannabis use-related consequences are an outcome of cannabis use behaviors, it is important to classify patterns of use with indicators that are solely descriptive of such use, rather than the outcomes. In other words, in order to classify how individuals use cannabis in the real world, it is essential to separate these indicators from the outcomes of use in order to evaluate whether consequences vary across these different patterns. This permits systematic examination of whether certain use patterns (including frequency, quantity, product, and mode) predict greater cannabis-related consequences and CUD symptomatology.

1.1. Current study

The current study used latent class analysis (LCA) to classify use patterns across a range of cannabis products (plant, concentrates, and edibles) along with frequency (days per month), modes, and average hours "high" per day to provide the most comprehensive classification of cannabis use behaviors to date[1]. We hypothesized that monthly frequency, product, mode, and hours high per day would distinguish classes. We examined how each class differed on important demographics characteristics, state where campus is located (varying legal status), cannabis consequences, and CUD symptomatology. We hypothesized that classes with more monthly use frequency, concentrate use, hours high per day, and use modes would report greater consequences and CUD symptomatology. Analyses were completed in a sample varying widely in frequency of cannabis use (light to heavy users), permitting the characterization of a full range of cannabis users.

2. Material and methods

2.1. Participants

Past-year alcohol- and cannabis-using students 18–24 years old from three state universities (N = 1390) completed an online survey. Each state had different laws regarding recreational cannabis use (School A: illegal; School B: decriminalized; School C: legal for adults 21 and older). All three states had legal medicinal cannabis use. Recruitment was completed such that in the fall of 2017, 24,000 students (8000 at each of 3 universities) randomly chosen by each school's registrar were sent email invitations to participate in an online screening survey. A total of 7000 students completed the screening survey. The screening sample was fairly representative of the invited sample in terms of demographic characteristics provided by the registrars (White et al., 2019). Out of those screened, 2874 students met study eligibility criteria for the baseline survey. These criteria included the following: (i) being enrolled full-time at one of the three universities, (ii) being between ages 18 and 24; (iii) having used both alcohol and cannabis in the past year; (iv) being on the registrar's list as validated by email addresses in the contact information; and (v) having provided contact information. From the 2874 eligible students, we invited a random sample of 2501 students stratified by school to take the baseline survey. We over-sampled students who had used alcohol and cannabis in the past month to ensure that enough students were eligible for the second phase of this study (which collected daily data). A total of 1524 students (60.9% of those invited) completed the baseline survey, but only 1498 had usable data due to technical issues. Of these, 1390 provided data consistent with the eligibility criteria and comprise the final study sample (30.6% School A, 34.5% School B, and 34.9% School C). Additional recruitment and sample details are available in White et al. (2019) and sample description is shown in Table 1. All procedures were approved by the Brown University institutional review board and a Certificate of Confidentiality was obtained from NIDA.

2.2. Measures

2.2.1. Demographic characteristics

Students self-reported age (continuous), birth sex, race (recoded into non-Hispanic white versus all other race/ethnicities combined as the reference group), and university (dummy variables for School A and B, with School C as the reference).

[1] Quantity was not considered in this LCA due to the significant distinctions in units, potency, and administration that makes comparison across products imprecise. Instead, we included average "hours high per day" as an additional indicator of use in the analysis.

Table 1
Sample characteristics.

Sex **(n [%])**	
Male	522 (38)
Female	868 (62)
Age (*M [sd]*)	19.84 (1.34)
Race (n [%])	
American Indian	6 (0.43)
Asian	176 (13)
Black	47 (3)
Pacific Islander	8 (1)
White	962 (69)
Other	54 (4)
More than 1	136 (10)
Ethnicity (n [%])	
Hispanic/Latinx	170 (12)
School (n [%])	
A (illegal)	425 (31)
B (decriminalized)	480 (34)
C (legal 21 +)	485 (35)
Past 30-day cannabis frequency (*M [sd]*)	7.75 (9.88)
Plant users; (n [%])	1315 (95)
Plant quantity (grams per day) (*M [sd]*)	2.91 (1.92)
Concentrate users; (n [%])	614 (44)
Concentrate hits per day (*M [sd]*)	3.45 (2.53)
Edible users; (n [%])	877 (63)
Edibles per day (*M [sd]*)	2.90 (1.39)
Hours high on use day (*M [sd]*)	4.93 (5.03)
Number of consequences (*M [sd]*)	3.01 (3.92)
CUDIT-R score (*M [sd]*)	6.70 (5.61)
Past 30-day alcohol frequency (*M [sd]*)	6.26 (5.33)
Access to cannabis (n [%])	
Probably impossible	9 (1)
Very difficult	24 (2)
Fairly Difficult	106 (7)
Fairly easy	621 (45)
Very easy	630 (45)

Note. (N = 1390), Past-30-day alcohol and past 30-day cannabis frequency refers to number of days.

2.2.2. Cannabis use behavior sample indicators

Participants self-reported cannabis use behaviors. To obtain categorical indicators for the LCA (see below), we dichotomized or trichotomized cannabis use behaviors to create generally equal-sized group indicators.

30-day Frequency. "How many days did you use marijuana in the past 30 days?". This continuous variable was transformed into three binary variables in order to be used for the LCA: low frequency: 0–1 times per month (39.0%), moderate frequency: 2–9 times per month (31.0%,), and high frequency: 10 or more times per month (30.0%). Variables for moderate and high frequency only were included in the LCA to prevent redundancies.

Modes. "What methods do you use?" Number of modes was summed across all 10 possible modes (joint, blunt, hand pipe, water pipe [including bong], hookah, one hitter, vape pen, ingest, dab/dab rig, and "other") and transformed into more (45.2%) or less than/equal to (54.8%) four modes. "Ingest" is included here (to refer to the oral consumption of cannabis products) in addition to the assessment of edible use as a product, as they uniquely characterize both a product and a mode of use.

Average hours high per day. "*Think about a typical week in the past month. How many hours were you high from marijuana each day of the week during a typical week in the past month?*". This item presented each day of the week (Monday – Sunday) with a continuous response scale in which participant moved an indicator from 0 to 12+ to indicate the typical hours high for each day of the week. Participants were instructed to choose "0" for days they *"did not typically use marijuana during a typical week"*. Time spent high per day was calculated across seven days (average hours per day divided by number of days used) and transformed to binary variable reflecting an average of greater than (62.0% of the sample) or less than/equal to (38.0%) four hours high per day.

Product use. "*What forms of marijuana do you use?*". These variables were coded as binary (0/1) for use of each product (plant, concentrate, edible).

2.2.3. CUD symptomatology

The 8-item Cannabis Use Disorders Identification Test – Revised (CUDIT-R) indexed CUD symptomatology (Adamson et al., 2010). Participants self-reported cannabis use and problems in the past 6 months on a 5-point Likert scale, with total scores ranging from 0 to 32, $\alpha = 0.77$. Scores of eight or more indicate hazardous cannabis use, and scores of 12 or more indicate potential for a CUD.

2.2.4. Cannabis consequences.

A list of consequences was taken from two validated measures: the 21-item Brief Marijuana Consequences Questionnaire (MACQ; Simons, Dvorak, Merrill, & Read, 2012) and the 24-item Brief Young Adult Alcohol Consequence Questionnaire (BYAACQ; Kahler, Strong, & Read, 2005), resulting in 28 unique cannabis consequences from which a sum score was computed. Example items included: *"found it difficult to limit cannabis use", "took foolish risks due to cannabis", "drove a car under influence of cannabis"*.

2.3. Data analysis

We calculated descriptive statistics using (R Core Team, 2013). We used Mplus (Muthén & Muthén, 2017) to conduct LCA models examining underlying classes based on cannabis use patterns reported above. LCA models provide probability of class membership for each respondent and item response probabilities for each latent class. We compared successions of LCA models with one to six-classes on several fit statistics (Akaike information criterion [AIC], Bayesian information criterion [BIC], and entropy) to identify the most parsimonious model with adequate fit. Most likely class membership was extracted only for the purposes of comparing mode prevalence across classes (Supplementary Table 1). Logistic regression analysis within Mplus was used to enter covariates (sex, age, race, school) in separate models to predict probability of class membership, with Bonferroni corrections used to account for multiple comparisons (corrected $\alpha = 0.001$ [0.05/40]). Finally, we examined class differences in cannabis consequences and CUDIT-R scores using a manual 3-step approach adjusting for class membership with outcomes, allowing for pairwise comparisons using Wald χ^{2}-tests by reference group alteration. Step 1 (MPlus) of this approach involves fitting the latent class model, Step 2 (manual) requires calculation of measurement error using the most likely class membership by latent class, and Step 3 (MPlus) involves using the calculated measurement error values calculated in Step 2 to estimate the association between the distal (auxiliary) outcome by latent class membership (Asparouhov & Muthén, 2014).

3. Results

3.1. Sample descriptives

Demographic and cannabis-related characteristics are provided in Table 1.

3.2. LCA

3.2.1. Number of classes and class characteristics

Models with seven or more classes failed to converge. Fit statistics for the 1- through 6-class solutions are provided in Table 2. Model fit improved through the addition of a fifth class, which was ultimately chosen based on BIC and LRT. Although not the highest entropy, the 5-class solution exhibited excellent entropy and (unlike the 6-class

Table 2
Fit statistics for LCA.

# of classes	AIC	BIC	SBIC	Entropy	LL	LRT
1	11118.07	11154.73	11132.5	–	−5552.04	–
2	10266.56	10345.11	10297.46	0.995	−5118.28	852.786***
3	9967.824	10088.28	10015.21	0.868	−4960.91	309.390***
4	9901.556	10063.91	9965.43	0.929	−4919.78	80.885***
5	**9858.174**	**10062.42**	**9938.532**	**0.868**	**−4890.09**	**58.369*** **
6	9846.727	10092.87	9943.568	0.834	−4876.36	27.001*

Note. Selected model in bold. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, SBIC = Sample-size adjusted BIC, LL = Log-likelihood; LRT = Lo-Mendell-Rubin Adjusted Likelihood Ratio Test; * $p < .05$, ** $p < .01$, *** $p < .001$.

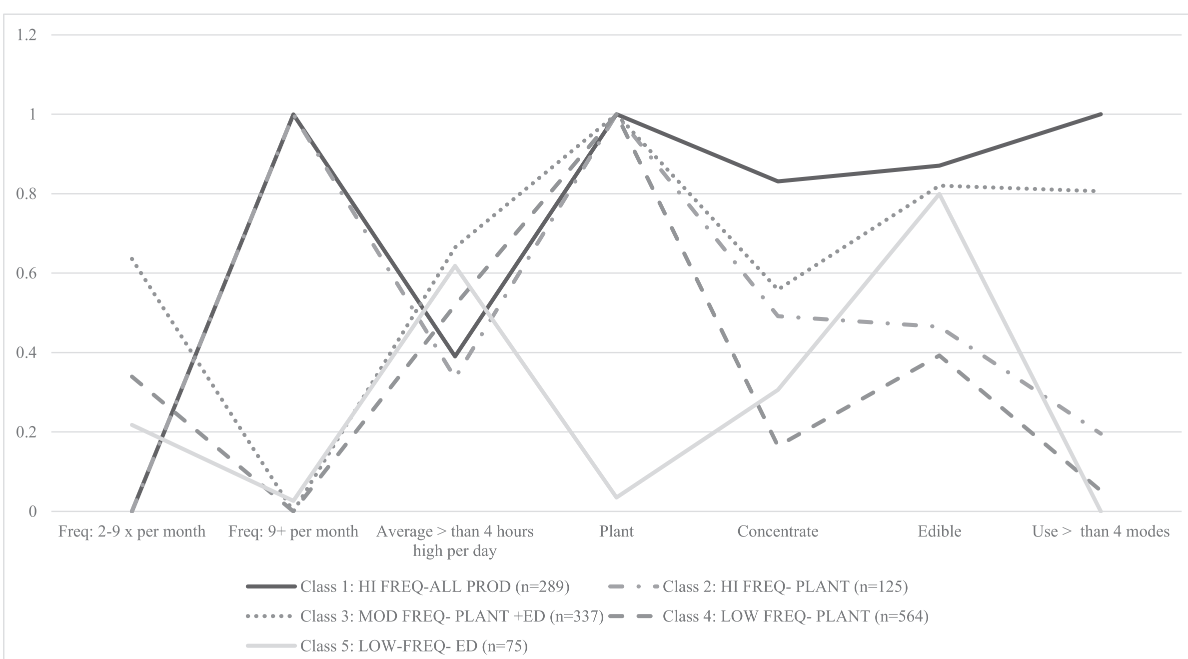
solution) had good differentiation between indicators across classes and was thus selected. Item probabilities for all five classes are presented in Fig. 1. Based on inspection of endorsement rates across indicators (with 'frequency' referring to number of days in the past 30 days), five classes can be characterized: 1) high-frequency users most likely to use all-products and more than four modes, with lower likelihood of being high more than 4 hours per day (HI FREQ-ALL PROD: 21%); 2) high-frequency users most likely to use plant, also moderately likely to use concentrates and edibles, more likely to use a low number of modes, and had the lowest likelihood of spending more than 4 hours high per day (HI FREQ-PLANT: 9%); 3) moderate-frequency users most likely to use plant and edibles, but also moderately likely to use concentrates, moderately likely to use a high number of modes, and most likely to spend more than 4 hours high per day (MOD FREQ-PLANT + ED: 24%); 4) low-frequency, mostly plant users moderately likely to use edibles, a low number of modes, and to spend more than 4 hours per day high (LOW FREQ-PLANT: 41%); and 5) low-frequency, primarily edible users, moderately likely to use concentrates, least likely to use a high number of modes, and more likely to spend more than four hours per day high (LOW FREQ-ED: 5%).

3.2.2. Demographic predictors and descriptives by class membership

Results of logistic regressions comparing classes on sex, age, race, and school (reflecting cannabis legalization status) are presented in Table 3. Significant differences were found for race (Class 5 [LOW FREQ-ED] less likely to be a race other than non-Hispanic white compared to Class 1 [HI FREQ-ALL PROD]), sex (Class 4 [LOW FREQ-PLANT] less likely than Class 1 to be female), and school (Classes 3 [MOD FREQ- PLANT + ED] and 5 less likely to attend school B (vs. school C) compared to Classes 1 and 2 [HI FREQ-PLANT]; Class 4 less likely to attend school B (vs. school C) compared to Class 2; Class 5 also less likely to attend school B (vs. school C) compared to Classes 3 and 4) but not age. We also descriptively examined the number of participants that reported use of each mode individually within classes (Supplementary Table 1).

3.2.3. Class differences in distal outcomes

Classes were compared on cannabis-related outcomes. Full results are presented in Table 4. Class 1 (HI FREQ-ALL PROD) reported the highest number of consequences, followed by Class 2 (HI FREQ-PLANT), and were not significantly different from each other. Class 1 reported significantly higher consequences compared to Class 3 (MOD FREQ- PLANT + ED), Class 4 (LOW FREQ- PLANT), and Class 5 (LOW FREQ-ED). Further, Class 2 (HI FREQ-PLANT) reported significantly more consequences than Classes 4 and 5. Class 3 (MOD FREQ-PLANT + ED) also reported a higher number of consequences than Class 4 (LOW FREQ- PLANT) and Class 5 (LOW FREQ-ED). Classes 4 and 5 did not differ significantly and reported the lowest number of consequences. Regarding CUDIT-R scores, again class 1 (HI FREQ-ALL PROD) reported the highest average CUDIT-R scores, followed by Class 2 (HI FREQ-PLANT), Class 3 (MOD FREQ- PLANT + ED), Class 5 (LOW FREQ-ED), and Class 4 (LOW FREQ- PLANT) respectively. All classes differed significantly from each other on CUDIT-R, except for Classes 4



	Freq (2-9)	Freq (10+)	>4 hrs high	Plant	Concentrate	Edible	>4 modes
Class 1: Hi Freq-All Prod (21%)	Low (0)	High (.99)	Mod (.39)	Highest (1)	Highest (.83)	Highest (.87)	Highest (.99)
Class 2: Hi Freq-Plant (9%)	Low (0)	High (.99)	Lowest (.34)	Highest (1)	Mod (.49)	Low (.47)	Low (.20)
Class 3: Mod Freq-Plant+Edibles (24%)	Mod (.64)	Low (0)	Highest (.65)	Highest (1)	Mod (.56)	High (.82)	High (.81)
Class 4: Low Freq-Plant (41%)	Low (.34)	Low (0)	Mod (.52)	Highest (1)	Lowest (.16)	Lowest (.39)	Low (.05)
Class 5: Low Freq-Edibles (5%)	Low (.22)	Low (.03)	Mod (.62)	Lowest (.03)	Low (.31)	High (.80)	Lowest (0)

Fig. 1. Five class solution *Note.* Values in bottom table indicate specific item response probabilities.

Table 3
Logistic Regression Odds Ratio for Covariates in LCA.

	2: HI FREQ-PLANT		3: MOD FREQ PLANT + ED		4: LOW FREQ-PLANT		5: LOW FREQ-ED	
Reference Class	OR	*p*	OR	*p*	OR	*p*	OR	*p*
	Sex (ref: Male)							
Class 1: HI FREQ-ALL PROD	1.37	0.19	1.53	0.02	**0.46**	**< 0.001**	1.62	0.08
Class 2: HI FREQ-PLANT	–	–	1.12	0.63	0.63	0.05	1.18	0.60
Class 3: MOD FREQ-PLANT + ED	–	–	–	–	0.71	0.08	1.05	0.85
Class 4: LOW FREQ-PLANT	–	–	–	–	–	–	0.75	0.29
	Race (ref: non-Hispanic white)							
Class 1: HI FREQ-ALL PROD	0.73	0.38	0.65	0.07	1.67	0.02	**0.29**	**< 0.001**
Class 2: HI FREQ-PLANT	–	–	0.88	0.69	1.23	0.50	0.40	0.01
Class 3: MOD FREQ-PLANT + ED	–	–	–	–	1.08	0.74	0.45	0.01
Class 4: LOW FREQ-PLANT	–	–	–	–	–	–	0.49	0.01
	Age							
Class 1: HI FREQ-ALL PROD	1.08	0.52	1.07	0.34	1.03	0.65	1.16	0.20
Class 2: HI FREQ-PLANT	–	–	0.99	0.98	1.11	0.23	1.08	0.56
Class 3: MOD FREQ-PLANT + ED	–	–	–	–	1.11	0.12	1.08	0.49
Class 4: LOW FREQ-PLANT	–	–	–	–	–	–	1.20	0.10
	School A (ref: C)							
Class 1: HI FREQ-ALL PROD	1.01	0.98	1.02	0.92	1.17	0.48	0.73	0.25
Class 2: HI FREQ-PLANT	–	–	1.02	0.96	1.17	0.63	0.72	0.33
Class 3: MOD FREQ-PLANT + ED	–	–	–	–	1.15	0.54	0.71	0.21
Class 4: LOW FREQ-PLANT	–	–	–	–	–	–	0.62	0.05
	School B (ref: C)							
Class 1: HI FREQ-ALL PROD	1.29	0.44	**0.52**	**< 0.001**	0.67	0.01	**0.24**	**< 0.001**
Class 2: HI FREQ-PLANT	–	–	**0.40**	**< 0.001**	**0.52**	**< 0.001**	**0.18**	**< 0.001**
Class 3: MOD FREQ-PLANT + ED	–	–	–	–	1.28	0.33	**0.45**	**0.001**
Class 4: LOW FREQ-PLANT	–	–	–	–	–	–	**0.35**	**< 0.001**

Note. School A = Illegal, School B = Decriminalized, School C = Legal. ORs represent comparisons between classes specified in columns versus reference classes specified in rows.

Table 4
Mean comparison of outcomes for LCA.

			2: HI FREQ-PLANT		3: MOD FREQ PLANT + ED		4: LOW FREQ-PLANT		5: LOW FREQ-ED	
Reference Class	*M*	*SE*	Wald	*p*	Wald	*p*	Wald	*p*	Wald	*p*
	Cannabis Consequences									
Class 1: HI FREQ-ALL PROD	5.93	0.27	1.62	0.20	**21.61**	**< 0.001**	**176.90**	**< 0.001**	**157.13**	**< 0.001**
Class 2: HI FREQ-PLANT	5.30	0.40	–	–	3.80	0.05	**47.21**	**< 0.001**	**43.35**	**< 0.001**
Class 3: MOD FREQ-PLANT + ED	3.23	0.18	–	–	–	–	**66.48**	**< 0.001**	**55.70**	**< 0.001**
Class 4: LOW FREQ-PLANT	0.17	0.03	–	–	–	–	–	–	1.02	0.31
Class 5: LOW FREQ-ED	0.37	0.19	–	–	–	–	–	–	–	–
	CUDIT-R									
Class 1: HI FREQ-ALL PROD	12.63	0.34	**5.16**	**0.02**	**20.65**	**< 0.001**	**61.87**	**< 0.001**	**52.66**	**< 0.001**
Class 2: HI FREQ-PLANT	10.78	0.43	–	–	**4.67**	**0.03**	**28.72**	**< 0.001**	**22.44**	**< 0.001**
Class 3: MOD FREQ-PLANT + ED	6.02	0.47	–	–	–	–	**112.72**	**< 0.001**	**5.35**	**0.02**
Class 4: LOW FREQ-PLANT	1.72	0.99	–	–	–	–	–	–	2.36	0.12
Class 5: LOW FREQ-ED	2.71	0.33	–	–	–	–	–	–	–	–

Note. Test statistics from Wald chi-square difference tests. ORs represent comparisons between classes specified in columns versus reference classes specified in rows.

and 5.

3.3. Supplemental analyses

We conducted a supplemental LCA on a subset of the sample who used only plant products (N = 330). This subsample was explored separately in order to demonstrate the solution that is derived when assuming only plant-based use, and to highlight the importance of assessing the full range of cannabis products. One indicator for the LCA was number of days of cannabis use in the past month (trichotomized as above). We also included a measure of the number of sessions of dry leaf cannabis a day, derived from the Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Use Inventory (DFAQ- CU: Cuttler & Spradlin, 2017). This variable was dichotomized into one session per day (75.6%) vs. more than one session per day (24.4%). We included a measure of quantity, which was transformed to a binary variable indicating greater than (49.1%) or less than/equal to (50.9%) 1/8 g daily. Modes of use were dichotomized (yes, no) for use of each of seven plant product modes (i.e., joint, blunt, hand pipe, water pipe [including bong], hookah, one hitter, vape pen).

The LCA of plant-only users suggested two distinct classes of heavy and light users (see Supplemental Fig. 1). These classes did not differ on major demographic factors. Heavy users reported significantly more consequences and higher CUDIT-R scores compared to light users (see Supplemental Materials). These results were consistent with previous attempts to classify cannabis users based on a single product, which found classes primarily differentiated by degree, not products or modes of use (Pearson, Bravo, & Conner, 2017; Taylor et al., 2017). This simple solution further illustrates the importance of examining multiple-products (concentrates and edibles as well as plant) when characterizing cannabis use patterns.

4. Conclusions

This study aimed to classify cannabis users with a comprehensive examination of use behaviors and patterns. Consistent with the changing culture of cannabis use and heavy rates among college students (Schulenberg et al., 2018), most of our sample (76%) engaged in use of products besides plant, highlighting the importance of examining complex cannabis use patterns. Results suggested five unique classes distinguished on past 30-day frequency, products, and modes. Overall, results indicate that complex cannabis use patterns among college students can be classified by multiple behavioral indicators.

Results identified meaningful classes that were derived on the basis of cannabis use behaviors. The high-frequency all-product use class reported the highest CUDIT-R scores and differed significantly from all other classes. This class also had the highest number of consequences, which differed significantly from all classes except the high frequency primarily plant users. These findings suggest that monthly frequency (i.e. number of days used in the past 30) remains a robust predictor of cannabis-related consequences and problems. Consistent with other studies demonstrating that higher risk is associated with concentrates among adult users (Bidwell et al., 2018), the high-frequency all-product class reported higher CUDIT-R scores than the high-frequency plant class, supporting increased risk for heavy use and related problems from these products.

While traditional cannabis (i.e., plant) use has been consistently related to consequences, the findings presented herein suggest that use of additional products increases risk. This may be attributed to a multitude of factors including elevated potency, ease of use, and duration of effects. Highly elevated potency in other products (e.g., concentrates) leads to significant increases in impairment, intoxication, and duration of effects. Portability and concealability of administration mode (e.g., vaporizer) has been linked with use in potentially hazardous situations (e.g., while driving) and in locations wherein traditional cannabis use is prohibited (Aston, Farris, Metrik, & Rosen, 2019). Finally, duration of the effects of plant use typically lasts between 1 and 2 hours depending on THC potency. However, intoxicative effects from certain products (e.g., edibles) may last upwards of 6–7 hours or longer depending on the number of mg of THC ingested, significantly increasing the time over which consequences may occur. Further, CUDIT-R scores in the high frequency-all product class were indicative of potential CUD, whereas scores in the high-frequency plant class reflected only hazardous cannabis use (Adamson et al., 2010). Therefore, although frequency (i.e., number of days used) remains important, assessing additional product use is necessary when examining CUD symptomatology. Future studies should examine how classes of cannabis users may differ on specific CUD symptoms. For example, it may be that concentrate users are more likely to develop tolerance or experience withdrawal due to the high THC potency of these products.

Our classes are somewhat consistent with Krauss et al. (2017), who found latent classes of light plant users, heavy plant users, heavy plant and concentrate users, and light plant and edible users among adult cannabis users. Our results extend these findings by also identifying a high-frequency all-product (plant, concentrate, and edible) group, as well as a moderate frequency plant-based group. Although average hours high per day did not strongly differentiate classes compared to product, mode, and past 30-day frequency, we did observe some class differences. Despite using at a higher 30-day frequency and more products and modes, our high-frequency all-product class was less likely to report more hours high per day. This may reflect increased tolerance resulting from high-frequency compared to low frequency use (Jones, Benowitz, & Bachman, 1976; Newmeyer, Swortwood, Abulseoud, & Huestis, 2017). In accordance with this interpretation, the next group of high-frequency mostly plant users was also less likely to endorse spending more than four hours high per day (consistent with their use of fewer modes overall). Alternatively, it is possible that the term “high” was interpreted differently by students in this study compared to other adult cannabis users. Despite this possibility, well-validated measures administered to college student samples use the term “high” to assess for norms and perceptions of intoxication among this population (Pearson, Liese, Dvorak, & Marijuana Outcomes Study Team, 2017). Finally, the smallest group (low-frequency primarily edible users) was likely to spend more than four hours high per day, potentially due to lower tolerance, or the delayed onset of effects and extended intoxication that results from edible use (Barrus et al., 2016).

Several demographic characteristics distinguished the classes as well. Compared to the largest class (low-frequency plant users), the high-frequency all product class was more likely to be male. The high-frequency all-product class was also more likely to be white compared to the low frequency edible class. With regard to school differences, we would have expected that students attending school in the state with legalized recreational marijuana use (school C) versus schools in states where marijuana was illegal (school A) or decriminalized (school B) would be more likely to be in the multiple product class as compared to the primarily plant classes, given easier access to a variety of products on the legal market. However, there was no difference between the two frequent classes (multiple products versus plant); nor was there a difference between the frequent multiple product class and the low plant class when comparing either schools in states with illegal or decriminalized marijuana to the school in the state with legalized marijuana. However, students attending school in the state where recreational marijuana use is legal were more likely to be in the two edible classes (versus all other classes) than those attending school in the decriminalized state. The low-frequency edible class was more likely to attend the school in the state with legalized recreational marijuana (school C) than the school in the state where marijuana use is decriminalized (school B) compared to all groups. At the time of the study, schools A and B were not near other states where recreational cannabis was legal so physical proximity to recreational cannabis outlets cannot explain their higher or equal rates of all-product users. Instead, it is possible that the low mean age of the sample, access to cannabis products via other means (e.g., direct purchase from growers), and the requirement to be 21 to purchase cannabis recreationally in that state could explain why we did not consistently find multiple product users to be more likely attend school C. It is also possible that campus norms were more salient to users than state laws. For example, ease of access to cannabis did not account for differences between schools, suggesting that additional factors such as school norms or racial composition may have accounted for these school-level differences (see White et al., 2019). Other studies have shown that state-level policy may not impact cannabis norms or perception of risk (Blevins et al., 2018). Racial composition of the sample may have had a significant impact, as there were significantly more Asian students compared to white students in school C than school B, and frequency of cannabis use among White students is much higher compared to Asian students (White et al., 2019). We did find, however, that the low-frequency edible group was more likely to attend school C, compared to B, suggesting they may be taking advantage of increased accessibility of edible products due to legalization.

4.1. Strengths and limitations

The current study was based on a large multi-site sample of college student cannabis users and is the most comprehensive classification of users based only on cannabis use behaviors to date. This is a critical sample in which to examine patterns of cannabis use, as rates of use and experimentation with additional products and modes increases during the college years (Jones, Hill, Pardini, & Meier, 2016; Odani et al., 2019). We took a rigorous approach to determining whether specific patterns of use differed based on external correlates, which reduced classification bias in that classes were uncontaminated by cannabis-related consequences and problems. Moreover, in assessing multiple cannabis modes and products, we highlighted the potential gap in knowledge when singular modes and products are assumed.

This research should be understood in the context of several limitations. First, we did not measure monthly frequency for each product individually. Additional detail regarding frequency of specific products would enhance the specificity of our analyses. For example, it is possible that the high-frequency all-product group was predominantly using concentrates over plant, contributing to higher reported CUDIT-R scores compared to the high-frequency plant group. Second, causality cannot be determined in cross-sectional studies. Future research should examine how distinct patterns of cannabis use prospectively predict consequences and development of CUD, although it is reasonable to expect that cannabis use is a precursor of consequences. Third, results from this sample may not translate to the general population of non-college attending adults, and our oversampling of past-year alcohol (and cannabis) users may not represent all cannabis users. We did not include alcohol use in the LCA, although, we have found that nearly all (99%) of our sample reported past 30-day drinking. We were also unable to examine differences among medicinal versus recreational users due to a small proportion of medicinal users (1.5%, n = 30), but future research should examine whether medicinal use is an important class indicator. Fourth, most of our sample was unable to report on average potency of plant cannabis (70% responded "I don't know"), suggesting methods other than self-report should be considered to measure potency in future studies. Fifth, an alternative analytic approach and area of future research would be to investigate indicators of cannabis use behavior in a single model, which may indicate the strongest predictors of consequences and CUDIT-R scores. Related, limitations of the CUDIT-R, which was developed as a screening tool and is best characterized as a single factor, would make it difficult to examine specific symptoms. Future studies should complete full diagnostic interviews in order to examine specific CUD symptoms. Finally, as there are a larger number of modes available for plant products, this may have reduced variability we saw in number of modes among classes that were not heavy plant users (e.g., edible users). Future studies may use additional analytic techniques in order to examine additional modes within product type. For example, in our study we used the term "ingest" to refer to the primary mode by which edible products are used. However, other studies have specifically assessed edible use of "food" products (Streck, Hughes, Klemperer, Howard, & Budney, 2019), but it is possible that individuals could ingest products other than traditional "food" (e.g., tinctures).

4.2. Conclusions

This study points to the importance of examining multiple products (concentrates and edibles as well as plant) when characterizing cannabis use and associated consequences. In addition to frequency of use at the daily level, use of multiple products is associated with additional risk of consequences and problems. Future research should examine these patterns in more diverse populations (e.g. non-college attending young adults) and longitudinally in order to fully understand patterns of risk associated with cannabis use, as well as other alcohol and substance use.

CRediT authorship contribution statement

Rachel L. Gunn: Writing - original draft, Conceptualization, Formal analysis. **Elizabeth R. Aston:** Conceptualization, Writing - review & editing. **Alexander W. Sokolovsky:** Writing - review & editing, Data curation. **Helene R. White:** Funding acquisition, Investigation, Supervision, Writing - review & editing. **Kristina M. Jackson:** Funding acquisition, Investigation, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.addbeh.2020.106329.

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