*Cannabis*
2023, Volume 6 (3)
© Author(s) 2023
researchmj.org
10.26828/cannabis/2023/000161

OPEN ACCESS

# Evaluation of the Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Use Questionnaire and its Relations to Cannabis-Related Problems

**Jordan A. Gette[1], Andrew K. Littlefield[2], Sarah E. Victor[2], Adam T. Schmidt[2], and Sheila Garos[2]**
[1]The Center of Alcohol and Substance Use Studies, Rutgers University
[2]Department of Psychological Sciences, Texas Tech University

## ABSTRACT

Cannabis use and the prevalence of cannabis use disorder (CUD) among emerging adults are on the rise. Several indicators of cannabis use (e.g., quantity, frequency) as they relate to negative outcomes have been posited in the extant literature. Despite research examining links between indicators and cannabis outcomes, few assessments of cannabis use indicators exist. The Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Use Inventory (DFAQ-CU) was developed to assess cannabis use across a range of factors. However, the factor structure of the DFAQ-CU has not been replicated. Further, the DFAQ-CU was modeled using reflective strategies despite formative strategies being conceptually appropriate. The present study utilized principal components analyses (PCA) and principal axis factoring (PAF) to evaluate the structure of the DFAQ-CU. PCA yielded a four-component solution; PAF resulted in a five-factor solution. Linear regression found significant relations between PCA components and PAF factors with CUD symptoms and cannabis-related problems; however, effect sizes were larger for the PAF suggesting possible misdisattenuation. The PCA components demonstrated evidence of discriminant and convergent validity with measures of cannabis and alcohol behavior. The study informs research and clinical work through the refinement of cannabis use assessment and enhancing our understanding of the importance of model selection.

**Key words**: = cannabis; structural equation modeling; assessment; principle components analysis; emerging adults

Prevalence of cannabis use among college-aged individuals is at a record high with 40.3% of emerging adults enrolled in college having used cannabis in the past year and 5.6% reporting daily use (Patrick et al., 2022). Previous work has demonstrated a host of deleterious cognitive (e.g., Lovell et al., 2020), academic (e.g., Meda et al., 2017; Phillips et al., 2015), and health (e.g., Russell et al., 2018) consequences associated with cannabis use. Perhaps most importantly, prevalence of cannabis use disorder (CUD) is rising. Notably, in a sample of college students reporting past month use, 54% met criteria for CUD (Schultz et al., 2019). Despite research noting a range of negative outcomes and increased rates of CUD, cannabis use attitudes have become more favorable over time (Gallup, 2021), particularly as cannabis becomes more widely available following shifts in policy over the last decade (Carliner et al., 2017; Roditis et al., 2016;

Corresponding Author: Jordan Gette, Ph.D., Rutgers University, 607 Allison Road Piscataway New Jersey 08854. Email: Jordan.gette@rutgers.edu

Wall et al., 2016). Thus, it is crucial to better understand which indicators of cannabis use most strongly relate to adverse outcomes among college students.

*Indicators of Cannabis Problems and Cannabis Use Disorder*

*Frequency.* Frequency of cannabis use is perhaps the most examined indicator of cannabis use problems (e.g., Pearson, 2019). Among those meeting criteria for CUD, the mean number of use days in the past year was 225.3 (Hasin et al., 2016), suggesting that those with CUD use cannabis on more days than not. A systematic review found that cannabis use in adolescence increases the likelihood of developing cannabis dependence in adulthood and that as frequency of use increases, risk for CUD development increases (Levine et al., 2017). Cannabis use frequency is significantly related to cannabis problems and CUD and this relation holds when controlling for quantity of use and age of onset (Callaghan et al., 2020; Zeisser et al., 2012). Although there is strong evidence to support the relation between cannabis use frequency and associated problems, there is still a significant portion of the variance in CUD that is unaccounted for. For example, approximately 83% of weekly cannabis users do not meet criteria for a CUD (Cougle et al., 2016), suggesting that frequency alone is insufficient to explain cannabis problems.

*Quantity.* Several studies have examined relations between quantity of cannabis used, cannabis-related problems, and CUD. As quantity of use increases, the odds of having CUD increase, even after controlling for frequency of use and age of onset (Callaghan et al., 2020). Further, past month quantity is significantly positively correlated with dependence symptoms (Lopez-Pelayo et al., 2021). Given difficulty in defining quantity, Zeisser et al. (2012) attempted to create a "standard joint" (i.e., 10 puffs on a joint, 5 hits on a bong or pipe, or 0.5 grams of cannabis). Using this means of assessment, increases in cannabis use quantity were significantly related to five cannabis use problem domains (social/financial/legal; failure to fulfill responsibilities; cannabis urge; concern by friends; and failure to reduce use). However, after controlling for frequency, quantity only remained a significant indicator of failure to fulfill responsibilities. Although promising evidence exists that quantity of cannabis use predicts cannabis use problems and CUD symptoms, more work is needed to understand the nuances of this relation, as single indicators of quantity are insufficient to fully capture the dynamic between quantity of use and associated problems.

*Age of Onset.* Another factor that may influence the experience of cannabis-related problems and CUD is age of onset (i.e., age of first cannabis use). Though recent work assessing age of onset is limited, several studies found that earlier age of onset (i.e., adolescence) is associated with increased odds of cannabis dependence (Lopez-Pelayo et al., 2021; Richmond-Rakerd, et al., 2016) and higher current frequency of use (Azagba & Asbridge, 2019). However, the relation between age of onset and cannabis-related problems may become non-significant when frequency is controlled for (Rioux et al., 2018). As such, it may be that the relation between age of onset and cannabis-related problems is mediated by frequency of use.

*The Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Use Inventory*

The Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Use Inventory (DFAQ-CU; Cuttler & Spradlin, 2017) was developed to improve assessment of cannabis use. This self-report measure is comprised of 24 core items and 17 screening items. Screening items are used to establish that participants have used cannabis in their lifetime, assess for medical reasons of use, and measure estimated tetrahydrocannabinol (THC) levels. Prior to factor analysis, only individuals that endorsed any lifetime cannabis use were retained. During reflective factor analysis (Cuttler & Spradlin, 2017), 22 of the 24 core items were retained across six factors: sessions per day, use frequency, age of use onset, quantity of loose-leaf cannabis use, quantity of cannabis concentrate use, and quantity of cannabis edible use (Figure 1). In a sample of college students in Washington state, these six factors accounted for 77% of available variance in cannabis use, with factor loadings ranging from .45 to .98. Correlations between factors ranged from -.23 to .52. Internal consistency estimates for the factors were as follows: frequency $\alpha = .95$, marijuana quantity α = .88, age of onset α = .81, cannabis concentrates α = .76, and daily sessions α = .69. The edible factor only contained one item, as such, internal consistency could not be calculated.

Strengths of the DFAQ-CU include assessment of methods of cannabis administration (e.g., loose leaf, edibles, concentrates) and pictures to aid individuals in reporting quantity. Though this is the first psychometrically robust self-report measure of cannabis quantity and frequency, it has yet to be evaluated outside of the original sample. Further, the current factor structure warrants discussion. Specifically, the quantity of edibles use factor is comprised of a single item, which can lead to difficulty specifying models and inability to assess reliability (e.g., Bollen et al., 1998). Additionally, the daily sessions factor is comprised of only two items and the internal consistency of this factor was in the "questionable" range (α = .69; Kline, 2013), while only three of the six factors resulted in Cronbach's alpha values in the "good" or "excellent" range (Kline, 2013). As such, it may be that the current factor structure of the DFAQ-CU has psychometric limitations that may warrant improvement.

### *DFAQ-CU: A Formative or Reflective Model?*

It is arguable that the modeling techniques used to develop the DFAQ-CU were inappropriate. The DFAQ-CU was developed by applying reflective latent variable modeling (principal axis factoring and maximum likelihood factor analyses; Cuttler & Spradlin, 2017). Reflective models, such as exploratory and confirmatory factor analyses, assume that a latent construct exists, and items are developed to address the construct (Borsboom et al., 2003). Conversely, formative factor analyses, such as principle components analysis, are, in essence, data reduction techniques (Borsboom, 2006) that posit that a collection of items can be reduced to create components. That is, the primary distinction is that formative models assume a latent variable is the outcome predicted by manifest indicators, whereas reflective models assume manifest indicators are the outcome predicted by the latent variable. In relation to the DFAQ-CU, cannabis use frequency, quantity, and age of onset are not likely to be preexisting constructs observed by assessing how often or how much an individual uses cannabis. Rather, it is more likely that items assessing these cannabis behaviors can be summarized as components in a meaningful way (Borsboom et al., 2003). That is, a factor of quantity does not exist prior to items assessing quantity of use. As such, formative analytic strategies are arguably more appropriate for the DFAQ-CU than reflective strategies (Borsboom et al., 2004; Coltman et al., 2007).

Beyond the above theoretical arguments against modeling the DFAQ-CU as reflective would result in construct invalidity, Rhemtulla et al. (2020) posit myriad problems that can occur when formative variables are modeled as reflective. Of chief importance for the present analyses, these authors note that using latent factors as opposed to composites can result in overestimation of item correlations as well as both the over- and under-estimation of model parameters (Rhemtulla et al., 2020). This occurs because latent modeling assumes that all non-shared variance in the model is unrelated to the measured construct, which ultimately results in misdissattenuation (i.e., overcorrection of "false measurement error;" Rhemtulla et al., 2020, p. 42) and bias due to overestimation of shared variance and the exclusion of unique variance across factors. Importantly, if items are not modeled correctly, relations among factors and other outcomes (e.g., cannabis-related problems) may not be accurate. Despite the original DFAQ-CU resulting in good model fit via reflective indices, it may still be theoretically and mathematically inappropriate.

### *The Current Study*

The purpose of this study is two-fold. First, the primary goal is to reevaluate the DFAQ-CU to determine if its structure holds in an independent sample using formative analyses and how different modeling approaches relate to cannabis use outcomes. Further, in addition to suboptimal modeling strategies, the DFAQ-CU was assessed in a state that had already passed recreational and medicinal cannabis laws at the time of evaluation. Evidence on the impacts of cannabis legalization is mixed, with studies of adolescent prevalence rates finding no difference (Carliner et al., 2017; Hasin et al., 2015; Hunt & Miles, 2015; Imbens & Wooldridge, 2009), but increases in cannabis prevalence in adults as a result of legality (Carliner, et al., 2017; Cerdá et al., 2012; Wen et al., 2015). Further, there is some evidence to suggest that different methods of use (e.g., wax, shatter, oils) may be more common in states in which cannabis is legal (Daniulaityte et al., 2015). As such, the structure of the DFAQ-CU may be different in states without legal cannabis, particularly the quantity of concentrates and quantity of edibles factors of the DFAQ-CU. The second aim is to determine if the components derived from the PCA demonstrate evidence of convergent and discriminant validity with existing measures of cannabis and alcohol behavior. The overarching goal of these aims is to discern the structure and utility of the DFAQ-CU as a measure of cannabis use behavior.

## METHODS

### *Participants*

A total of 442 participants ($M_{age}$ = 19.37, 68.33% female, 60.64% White, 21.76% Hispanic/Latinx) from a large public university in Texas were included in the present analysis. Individuals had to be at least 18 years old to participate and received course credit for their participation. The present study utilized a subset of participants from a larger study that endorsed lifetime cannabis use collected prior to COVID-19-related campus closures. Eligible participants were directed to an online survey database, Qualtrics (Qualtrics, 2015, Provo, Utah) to anonymously complete several measures regarding demographic information as well as measures assessing rates cannabis and alcohol use patterns. All procedures were approved by the university's Institutional Review Board.

### *Measures*

*Demographics.* Participants completed a baseline demographic measure assessing sex, gender, race, ethnicity, age, socioeconomic status, and other sociodemographic variables.

*The Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Use Inventory (DFAQ-CU; Cuttler & Spradlin, 2017).* The DFAQ-CU was used to assess cannabis use behaviors. As previously discussed, the DFAQ-CU is a self-report scale measuring frequency, quantity, and age of onset for cannabis use. The original scale, using reflective latent variable analyses, is comprised of 41 Likert-like items (24 core items and 17 screening items) with 22 of the 24 core items loading onto six factors of cannabis use behaviors: daily sessions, frequency, age of onset, loose-leaf quantity, concentrate quantity, and edibles quantity (Figure 1).

*Cannabis Timeline Follow-back.* A Timeline follow-back of past-two-week cannabis quantity and frequency was included to compare to assess for evidence of convergent validity of the DFAQ-CU (Pearson et al., 2017). Participants reported whether they used cannabis on a given day, method of administration, and quantity in grams. Three values were used in the present analyses: total use days, average weekend quantity, and average weekday quantity.

*Cannabis Consequences.* The Brief Marijuana Consequences Questionnaire (B-MACQ; Simons et al., 2012) was used to assess cannabis consequences. The B-MACQ is a self-report measure of cannabis-related problems experienced in the past six months developed from the 50-item Marijuana Consequence Questionnaire. The 21 dichotomous (yes/no) B-MACQ items are summed to create a total problem score (range: 0 to 21) with higher values representing more cannabis-related problems. The B-MACQ demonstrates excellent internal consistency and does not exhibit differential item functioning across biological sex (Simons et al., 2012).

*Cannabis Use Disorder Symptoms.* To assess for CUD symptomology, the symptoms of the DSM-5 CUD were presented as 11 dichotomous (yes/no) items with higher sum scores representing greater CUD symptoms in the past year. A similar approach has been used previously to assess CUD symptoms (e.g., Dierker et al., 2018).

*Alcohol Measures.* Alcohol frequency and binge drinking (4+/5+ drinks per occasion for women and men) were assessed using the NIAAA binge drinking questionnaire (NIAAA, 2004). This measure contains 10-items assessing past-year and past-two-week alcohol frequency, binge drinking, and quantity. To assess alcohol use disorder (AUD) symptoms, the DSM-5 AUD criteria were presented as 11 dichotomous (yes/no) items (American Psychological Association, 2013). Items are summed to create a total number of symptoms endorsed in the past 12 months.

*Analytic Approach*

PCA and PAF analyses were conducted in SPSS Version 25.0 (IBM Corp., Armonk, NY, USA). Confirmatory factor analyses and regressions were conducted in Mplus Version 7.31 (Muthén & Muthén, 1998-2015), and parallel analyses were conducted using R version 3.5.1 (R Core Team, 2018), consistent with our prior work using these techniques (Gette et al., 2022). Missing data patterns were analyzed using Mplus software. Of items that did not include skip logic, less than 1% of observations were missing. For PCA and PFA, pairwise deletion was used (Van Ginkel et al., 2014). Core DFAQ-CU items were transformed into z-scores to account for variability in response options across items (i.e., some items begin with 0, some with 1, some are alphabetical, some free response) and to be consistent with the original scoring (Cuttler & Spradlin, 2017).

Prior to analyses, data were screened to assess distribution, skew, kurtosis, outliers, and missing data patterns. Additionally, Kaiser-Meyer-Olin (KMO) testing was conducted in SPSS to ensure that the sample was appropriate for component analyses with values of .60 or greater considered acceptable (Kaiser, 1974). Additionally, Bartlett's (1950) Test of Sphericity was used to examine redundancy among items to ensure that creation of components is appropriate. A significant p-value (i.e., p < .05) indicates that variables are related and suitable for component analysis. Horn's (1965) parallel analysis was conducted to determine component and factor retention for both Principal Components Analysis (PCA) and Principal Axis Factoring (PAF; Velicer et al., 2000; Velicer & Jackson, 1990) using the fa.parallel function under the psych package in R (Revelle, 2020). This function was selected given its ability to handle missing data in its determination of the optimal number of components to retain. Horn's parallel analyses was conducted using a 95% confidence interval to avoid overfitting the data (Glorfeld, 1995). Prior to factor analyses, items were winsorized such that values exceeding 3.29 standard deviations above the mean were replaced to correspond to 3.29 standard deviations from the mean to minimize the influence of extreme values (e.g., consuming one ounce of cannabis per smoking session; Tabachnick et al., 2007). A total of 125 observations (0.67%) were winsorized.

Next, PCA and PAF were used to determine the optimal structures of the DFAQ-CU. PCA is a data-reduction technique in which items are combined linearly to extract components in order to account for the maximum possible variance in a set of items. PAF is a reflective modeling approach in which latent variables (or factors) are derived by determining the shared variance among a set of items to derive communalities and factor loadings, similar to exploratory factor analysis. PAF is most useful for reflective modeling when there are few indicators per factor or variability among number of indicators per factor (de Winter & Dodou, 2012). The original factorization of the DFAQ-CU resulted in six factors with one to nine items per factor, making PAF an appropriate method from this perspective. Both PCA and PAF models were conducted using a Promax rotated oblique solution (Dien, 2010) because it was expected that the factors and components would be correlated.

For each component/factor, individual items with factor or component loadings greater than .45 were retained (Kite & Whitely, 2018). Items were allowed to cross load if an item has a loading of .45 or greater on multiple factors. Next, Cronbach's alpha and omega were calculated to assess factors and component reliability (McDonald, 1999). Alpha values of .90 and above indicate excellent consistency, values of .80 to .89 are good, and .70 to .79 is acceptable (Kline, 2013). Additionally, to test the replicability of the PAF factors, H was calculated with values of .80 or greater indicating that the latent variable is well-defined (Hancock & Mueller, 2001; Rodriguez et al., 2016). Next, the models were compared to determine if these modeling techniques result in different structures and if so, which structure is most conceptually clear. To build evidence of convergent validity, the PCA components were correlated with existing measures of cannabis use and to were also correlated with measures of alcohol use to assess discriminant validity.

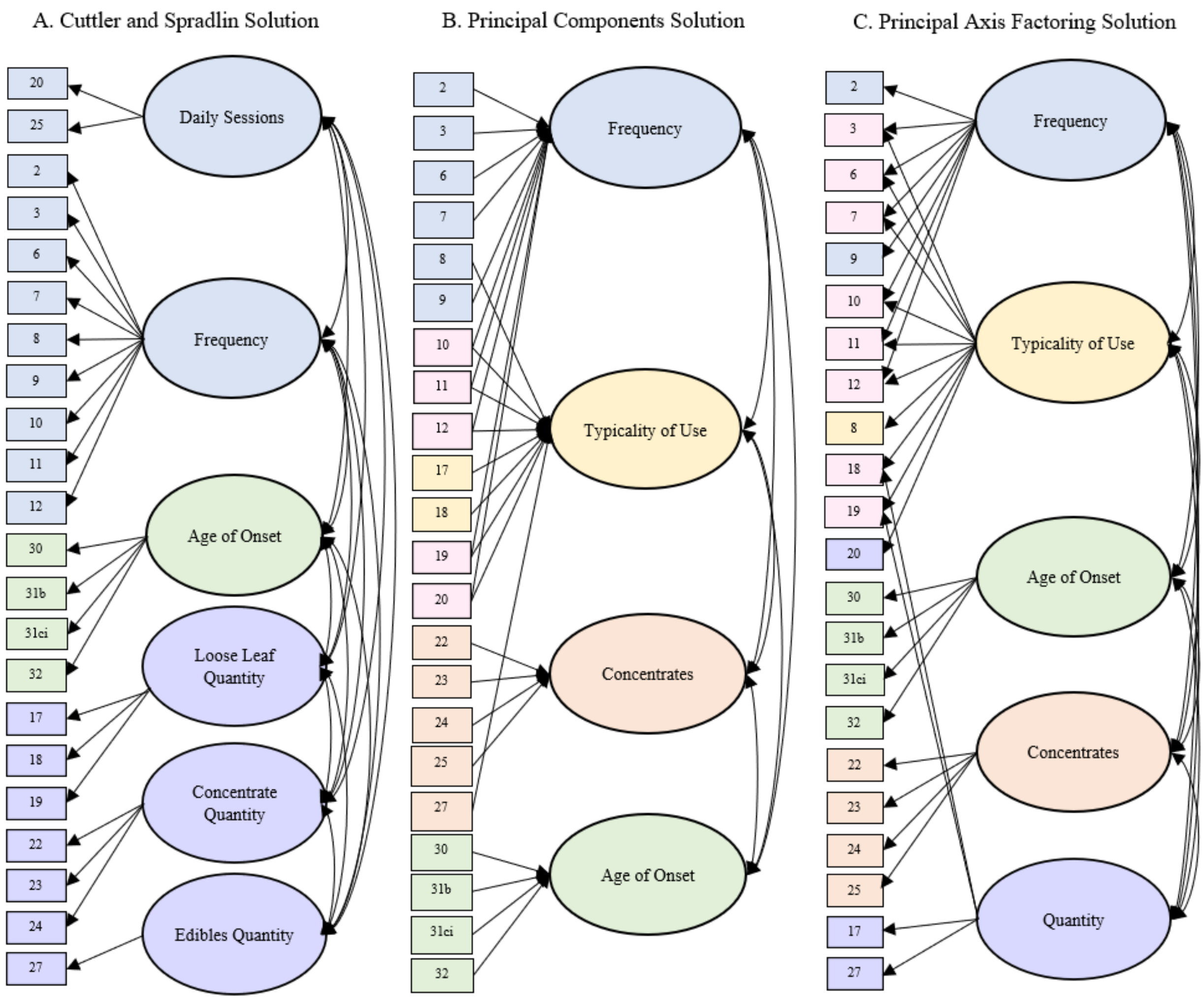
## RESULTS

Table 1 presents sample characteristics and DFAQ-CU item endorsements. KMO testing resulted in a value of .68 and a significant Bartlett's test of sphericity ($p < .001$), suggesting items were acceptable for components and factor analyses.

*Principal Components Analysis*

As indicated by Horn's parallel analysis, the PCA model was specified to include four-components using a Promax-rotated solution that accounted for 73.13% of the variance in cannabis use (see Table 2 and Figure 1). The Frequency component (e.g., "How many days of the past week did you use cannabis?") is comprised of 10 items with component loadings from .45 to .96 (see Table 3) with an alpha of .94. The Typicality of Use component (e.g., "How many times a day, on a typical weekend, do you use cannabis?") is comprised of nine items with component loadings from .45 to .93 and alpha of .91. The Concentrates component (e.g., "How many hits of cannabis concentrates did you personally take yesterday?") is comprised of four items with component loadings from .72 to .93 and an alpha of .76. Lastly, the Age of Onset component (e.g., "How old were you when you FIRST STARTED using cannabis regularly [2 or more times/month]?") is comprised of four items with component loadings from .76 to .89 and alpha of .87. Of note, all cross-loading of items were retained on the Frequency

Figure 1. *Comparison of Models Derived from the Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Inventory*




*Note.* PCA = principals components analysis, PAF = principal axis factoring. Colors correspond to factors and components with loadings ≥ .45. Blue corresponds to frequency, green corresponds to age of onset, purple corresponds to quantity, yellow corresponds to typicality of use, pink corresponds to items included on two components or factors.

Table 1. *Sample Characteristics and Descriptive Responses of the Core Items of the Daily Sessions, Frequency, Age of Onset and Quantity Use Questionnaire Prior to Transformations.*

| Sample Characteristics (N = 442) | |
|---|---|
| Age | 19.37 |
| Female | 68.33% |
| Non-Hispanic White | 60.64% |
| Hispanic | 21.76% |
| Cannabis Consequences M (SD) | 4.12 (4.46) |
| Cannabis Use Disorder Symptoms M (SD) | 1.91 (2.61) |
| DFAQ-CU Multiple Choice Items and Response Options | % Endorsement (N) |
| 2. Which of the following best captures when you last used cannabis? | |
| Over a year ago | 16.5 (73) |
| 9-12 months ago | 5.4 (24) |
| 6-9 months ago | 5.0 (22) |
| 3-6 months ago | 9.3 (41) |
| 1-3 months ago | 12.7 (56) |
| Less than 1 month ago | 13.1 (58) |
| Last week | 10.2 (45) |
| This week | 7.7 (34) |
| Yesterday | 12.2 (54) |
| Today | 2.3 (25) |
| I am currently high | 5.7 (25) |
| 3. Which of the following best captures the average frequency you currently use cannabis? | |
| I do not use cannabis | 0.0 (0) |
| less than once a year | 14.3 (63) |
| Once a year | 12.9 (57) |
| Once every 2-6 months (2-4 times/yr) | 4.5 (20) |
| Once every 2 months (6 times/yr) | 18.3 (81) |
| Once a month (12 times/yr) | 5.7 (25) |
| 2-3 times a month | 5.2 (23) |
| Once a week | 10.0 (44) |
| Twice a week | 5.2 (23) |
| 3-4 times a week | 9.5 (42) |
| 5-6 times a week | 4.5 (20) |
| Once a day | 4.1 (18) |
| More than once a day | 5.9 (26) |
| 6. How many days of the past week did you use cannabis? | |
| 0 days | 56.1 (162) |
| 1 day | 9.7 (28) |
| 2 days | 6.6 (19) |
| 3 days | 6.9 (20) |
| 4 days | 3.1 (9) |
| 5 days | 3.5 (10) |
| 6 days | 2.8 (8) |
| 7 days | 11.3 (33) |

| | |
|---|---|
| 8. Which of the following best captures the number of times you have used cannabis in your entire life? | |
| 1-5 times in my life | 14.9 (43) |
| 6-10 times in my life | 9.0 (26) |
| 11-50 times in my life | 20.4 (59) |
| 51-100 times in my life | 11.4 (33) |
| 101-500 times in my life | 17.6 (51) |
| 501-1000 times in my life | 10.7 (31) |
| 1001-2000 times in my life | 6.6 (19) |
| 2001-5000 times in my life | 4.5 (13) |
| 5001-10,000 times in my life | 3.5 (10) |
| more than 10,000 times in my life | 1.4 (4) |
| 9. Which of the following best captures your pattern of cannabis use throughout the week? | |
| I do not use cannabis at all | 41.3 (183) |
| I only use cannabis on weekends | 27.5 (122) |
| I only use cannabis on weekdays | 0.9 (4) |
| I use cannabis on weekends and weekdays | 30.2 (134) |
| 10. How many hours after waking do you usually first use cannabis? | |
| I do not use cannabis at all | 39.1 (173) |
| 12-18 hours after waking up | 17.6 (78) |
| 9-12 hours after waking up | 24.2 (107) |
| 6-9 hours after waking up | 7.9 (35) |
| 3-6 hours after waking up | 4.1 (18) |
| 1-3 hours after waking up | 3.4 (15) |
| Within 1 hour of waking up | 1.4 (6) |
| Within ½ hour of waking up | 1.4 (6) |
| Immediately upon waking up | 1.1 (5) |
| 32. Which of the following best captures the average frequency that you used cannabis before the age of 16? | |
| more than once a day | 0.7 (3) |
| once a day | 0.9 (4) |
| 5-6 times a week | 0.5 (2) |
| 3-4 times a week | 2.3 (10) |
| twice a week | 2.5 (11) |
| once a week | 1.1 (5) |
| 2-3 times a month | 4.5 (20) |
| once a month | 3.4 (15) |
| once every 2 months (6 times/yr) | 3.4 (15) |
| once every 3-6 months (2-4 times/yr) | 5.4 (24) |
| once a year | 3.2 (14) |
| less than once a year | 5.2 (23) |
| Never | 66.9 (295) |
| **DFAQ-CU Free Response Items** | **Mean (Range)** |
| 7. Approximately how many days of the past month did you use cannabis? | 7.16 (0.00 – 31.00) |
| 11. How many times a day, on a typical weekday, do you use cannabis? | 0.64 (0.00 – 10.00) |

| | |
|---|---|
| 12. How many times a day, on a typical weekend, do you use cannabis? | 1.13 (0.00 – 15.00) |
| 17. In a typical session, how much marijuana do you personally use? (in grams) | 0.69 (0.00 – 16.00) |
| 18. On a typical day you use marijuana, how much do you personally use? (in grams) | 0.66 (0.00 – 7.09) |
| 19. In a typical week you use marijuana, how much marijuana do you personally use? (in grams) | 2.33 (0.00 – 28.00) |
| 20. On a typical day you use marijuana, how many sessions do you have? | 1.18 (0.00 – 8.00) |
| 22. In a typical session you use cannabis concentrates, how many hits do you personally take? | 4.07 (0.00 – 30.00) |
| 23. On a typical day you use cannabis concentrates, how many hits do you personally take? | 5.20 (0.00 – 100.00) |
| 24. How many hits of cannabis concentrates did you personally take yesterday? | 1.65 (0.00 – 100.00) |
| 25. On a typical day you use cannabis concentrates, how many sessions do you have? | 1.55 (0.00 – 100.00) |
| 27. When you eat edibles how many milligrams of THC do you personally ingest in a typical session? | 75.15 (0.00 – 2000.00) |
| 30. How old were you when you FIRST tried cannabis? | 16.25 (12.00 – 21.00) |
| 31b. How old were you when you FIRST started using cannabis regularly (2 or more times per month for 6 months or longer)? | 17.29 (13.00 – 22.00) |
| 31ci. How old were you when you FIRST STARTED using cannabis on a daily or near daily basis? | 17.30 (14.00 – 21.00) |

*Note.* For items presented as multiple choice items, the percent endorsement for each response is listed. For free response items, the mean and range of response is listed.

Table 2. *Component Loadings of the Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Use Inventory using Principal Components Analysis*

| Item | Principal Component | | | |
|---|---|---|---|---|
| | Frequency | Age of Onset | Concentrates | Typicality of Use |
| 2. Which of the following best captures when you last used cannabis? | **.92** | -.02 | .23 | .15 |
| 3. Which of the following best captures the average frequency you currently use cannabis? | **.96** | -.10 | .12 | .17 |
| 6. How many days of the past week did you use cannabis? | **.88** | -.03 | .24 | .23 |
| 7. Approximately how many days of the past month did you use cannabis? | **.92** | -.02 | .20 | .24 |
| 8. Which of the following best captures your pattern of cannabis use throughout the week? | .39 | -.34 | -.13 | **.61** |
| 9. Which of the following best captures the number of times you have used cannabis in your entire life? | **.88** | -.10 | .05 | .07 |

| | | | | |
|---|---|---|---|---|
| 10. How many hours after waking up do you typically first use cannabis? | **.61** | -.29 | .09 | **.70** |
| 11. How many times a day, on a typical weekday, do you use cannabis? | **.82** | -.22 | .09 | **.45** |
| 12. How many times a day, on a typical weekend, do you use cannabis? | **.81** | -.15 | .04 | **.47** |
| 17. In a typical session, how much marijuana do you personally use? | .06 | .04 | .15 | **.61** |
| 18. On a typical day you use marijuana, how much do you personally use? | .35 | -.28 | .15 | **.93** |
| 19. In a typical week you use marijuana, how much marijuana do you personally use? | **.45** | -.23 | .10 | **.82** |
| 20. On a typical day you use marijuana, how many sessions do you have? | **.49** | -.37 | -.00 | **.80** |
| 22. In a typical session you use cannabis concentrates, how many hits do you personally take? | .11 | -.09 | **.93** | .06 |
| 23. On a typical day you use cannabis concentrates, how many hits do you personally take? | .05 | -.06 | **.84** | .12 |
| 24. How many hits of cannabis concentrates did you personally take yesterday? | .31 | -.06 | **.78** | .10 |
| 25. On a typical day you use cannabis concentrates, how many sessions do you have? | .11 | -.02 | **.72** | .15 |
| 27. When you eat edibles how many milligrams of THC do you personally ingest in a typical session? | -.25 | -.17 | .13 | **.66** |
| 30. How old were you when you FIRST tried cannabis? | -.32 | **.76** | -.10 | -.24 |
| 31b. How old were you when you FIRST STARTED using cannabis regularly (2 or more times/month)? | -.05 | **.89** | -.02 | -.33 |
| 31ci. How old were you when you FIRST STARTED using cannabis on a daily or near daily basis? | .18 | **.80** | -.12 | -.08 |
| 32. Which of the following best captures the average frequency that you used cannabis before the age of 16? | -.07 | **.85** | -.10 | -.06 |

*Note.* Bold text indicates that the item is included in the component as determined by component loadings ≥ .45.

and Typicality of Use components, suggesting overlap in these constructs. Correlations between components ranged from -.25 (Frequency and Age of Onset) to .90 (Frequency and Typicality of Use; see Table 3).

Items were included in any component in which the item exhibited a component loading of .45 or greater. As such, items 10 (typical hours awake before first use), 11 (typical sessions per weekday), 12 (typical sessions per weekend), 19 (typical weekly quantity), and 20 (typical daily sessions) were included on both the Frequency and Typicality of Use components. Although the present study applied names to the components, it should be highlighted that PCA components are not latent variables, and component naming in this context was used to facilitate discussion of outcomes, not to imply causality of manifest items and creation of latent variables (Borsboom, 2006; Fried, 2020).

Comparing DFAQ-CU components to a timeline follow-back measure of past month cannabis use, the Frequency, Concentrates, and Typicality of Use components yielded significant correlations with past month use days, average weekday quantity, average weekend quantity, cannabis consequences, and CUD symptoms with the largest correlations observed for the Frequency component followed by Typicality of Use (see Table 6). Interestingly, Age of Onset only resulted in a small, significant correlations with consequences and CUD symptoms, but not measures of quantity or frequency. Relations between DFAQ-CU components and measures of alcohol frequency, and alcohol binge frequency yielded small-to-negligible correlations with all components. There were no significant correlations between DFAQ-CU components and alcohol use disorder symptoms.

*Principal Axis Factoring* [1]

Using a Promax-rotated solution with five factors specified per parallel analysis, the PAF model resulted in solution accounting for 75.60% of the total variance (see Table 4). The Frequency factor (e.g., "How many days of the past week did you use cannabis?") is comprised of eight items with loadings from .51 to .97. The Typicality of Use factor (e.g., "On a typical day you use marijuana, how many sessions do you have?") is comprised of 10 items with loadings from .47 to .92. The Concentrates factor (e.g., "How many hits of cannabis concentrates did you personally take yesterday?") is comprised of four items with loadings from .65 to .92. The Age of Onset factor (e.g., "How old were you when you FIRST STARTED using cannabis regularly [2 or more times/month]?") is comprised of four items with loadings from .72 to .88. Finally, the Quantity factor (e.g., "In a typical session, how much marijuana do you personally use?") is comprised of four items with loadings from .58 to .85. Correlations between factors ranged from -.21 (Age of Onset and Concentrates) to .95 (Frequency and Typicality of Use; see Table 3).

The PAF model resulted in a high degree of cross-loading with 8 of 22 items loading onto two factors, primarily for Frequency and Typicality of Use factors (six items), followed by the Typicality of Use and Quantity factors (two items). Notably, all items that cross-loaded loaded onto the Typicality of Use factor and one other factor, suggesting that this factor may not be distinct when modeling the DFAQ-CU as reflective. This is further demonstrated by a correlation of .95 between the Frequency and Typicality of Use factors. Only the Concentrates and the Age of Onset factors did not demonstrate any cross-loading. The Frequency ($\alpha = .94$, $\omega = .95$) and Typicality of Use ($\alpha = .94$, $\omega = .93$) factors evinced excellent internal consistency. The Age of Onset factor ($\alpha = .86$, $\omega = .88$), and Quantity factor ($\alpha = .86$) demonstrated good consistency and the Concentrates factor ($\alpha = .75$, $\omega = .84$) was acceptable-to-good. H values for the factors ranged from .86 (Concentrates) to .98 (Quantity), suggesting that all PAF factors demonstrate replicability and are considered well-defined latent variables.

To assess the fit of the PAF model, a confirmatory factor analysis (CFA) was conducted for the solution, resulting in an RMSEA of .09 and a CFI of .86, suggesting suboptimal fit (Hu & Bentler, 1999). When the model was constrained such that items only loaded on to one component,

[1] Maximum likelihood factor analysis (MLFA) was also used as a reflective technique for the DFAQ-CU as MLFA tends to outperform PAF for models with unequal factor loadings (de Winter & Dodou, 2012). MLFA resulted in a similar factor structure as PAF, similar fit to the data per CFI and RMSEA, and similar relations with outcomes. However, MLFA had a greater number of items that cross-loaded (12 v. 8), accounted for less of the total variance for the DFAQ-CU, and had higher correlations between factors compared to PAF. As such, PAF was selected for comparison to the PCA.

model fit worsened (RMSEA = .10, CFI = .80). Additionally, a CFA was conducted with the present data using the solution generated in the original DFAQ-CU (Cuttler & Spradlin, 2017). This model resulted in an RMSEA of .10 and a CFI of .83, again suggesting poor fit to the data.

*Model Comparisons and Relations with Outcomes*

Mean scores for each participant on each component derived from the transformed data were used in the correlation analysis due to missing data attributable to DFAQ-CU skip logic on items related to age of onset and concentrate use. Examination of the relations among the PCA components and PAF factors found correlations ranging from -.27 to 1.00 (see Table 3). PCA components and PAF factors that tapped similar constructs (Age of Onset and Concentrates) showed correlations ranging from .92 to 1.00. Though the PAF model had similar factors as compared to the PCA component solution, the amount of cross-loading in the PAF model suggests differing outcomes as a result of modeling techniques with regard to simple structure (see Figure 1).

Ordinal linear regressions were conducted to determine relations between PCA components and cannabis-related consequences and use disorder symptoms (see Table 5). Examining cannabis consequences, the Frequency and the Typicality of Use components evinced medium, positive relations with cannabis consequences such that as frequency and typical levels of use (e.g., quantity in a typical day) increase, the number of consequences incurred increases. The Concentrates component evinced a small, positive relation cannabis consequences. Age of Onset evinced a small, negative relation with consequences such that earlier onsets of cannabis use was associated with greater number of consequences. Effect sizes ($r^2$) for these models ranged from .03 to .23. To determine if reflective modeling of formative variables results in overestimation of effects, univariate analyses were conducted to examine relations between PAF factors as they relate to cannabis consequences with PAF factors generally showing slightly larger effect sizes (see Table 5). In particular, the Age of Onset factor exhibited the largest differences: the PCA Age of Onset component resulted in an $r^2$ of .07 with consequences compared to an $r^2$ of .14 for PAF Age of Onset factor with consequences.

Similar patterns between PCA components and CUD symptoms emerged. The Frequency and the Typicality of Use components evinced medium, positive relations and the Concentrates component evinced small, positive relations with CUD symptoms. As with consequences, Age of Onset evinced a small, negative relation with CUD symptoms. Effect sizes ($r^2$) for these models ranged from .03 to .18 for CUD symptoms. Again, the PAF factors broadly showed larger effect sizes for relationships to both consequences and CUD symptoms (see Table 5). This difference was again most pronounced for the Age of Onset component with $r^2$s of .03 and .07 respectively.

Table 3. *Correlations between Principal Components Analysis Mean Values and Principal Axis Factoring Factor Scores.*

| Component or Factor | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1. PAF Frequency | - | | | | | | | | |
| 2. PAF Age of Onset | -.15 | - | | | | | | | |
| 3. PAF Concentrates | .36 | -.21 | - | | | | | | |
| 4. PAF Typicality of Use | .95 | -.20 | .39 | - | | | | | |
| 5. PAF Quantity | .57 | -.27 | .52 | .71 | - | | | | |
| 6. PCA Frequency | .99 | -.16 | .38 | .96 | .63 | - | | | |
| 7. PCA Age of Onset | -.15 | 1.00 | -.21 | -.20 | -.27 | -.16 | - | | |
| 8. PCA Concentrates | .36 | -.21 | 1.00 | .39 | .52 | .38 | -.21 | - | |
| 9. PCA Typicality of Use | .85 | -.25 | .40 | .92 | .84 | .90 | -.25 | .40 | - |

*Note.* PAF = principal axis factoring, PCA = principal components analysis. All correlations are significant at $p < .05$.

Table 4. *Item Loadings of the Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Use Inventory using Principal Axis Factoring*

| Item | Factor | | | | |
|---|---|---|---|---|---|
| | Frequency | Typicality of Use | Age of Onset | Concentrates | Quantity |
| 2. Which of the following best captures when you last used cannabis? | **.93** | .44 | .03 | .28 | .07 |
| 3. Which of the following best captures the average frequency you currently use cannabis? | **.97** | **.50** | -.05 | .18 | .04 |
| 6. How many days of the past week did you use cannabis? | **.89** | **.47** | .01 | .29 | .15 |
| 7. Approximately how many days of the past month did you use cannabis? | **.93** | **.52** | .04 | .26 | .12 |
| 8. Which of the following best captures the number of times you have used cannabis in your entire life? | .27 | **.70** | -.27 | -.01 | .26 |
| 9. Which of the following best captures your pattern of cannabis use throughout the week? | **.90** | .35 | -.07 | .07 | .07 |
| 10. How many hours after waking up do you typically first use cannabis? | **.51** | **.83** | -.23 | .19 | .38 |
| 11. How many times a day, on a typical weekday, do you use cannabis? | **.72** | **.79** | -.18 | .21 | .06 |
| 12. How many times a day, on a typical weekend, do you use cannabis? | **.71** | **.77** | -.05 | .16 | .09 |
| 17. In a typical session, how much marijuana do you personally use | .09 | .26 | -.05 | .13 | **.81** |
| 18. On a typical day you use marijuana, how much do you personally use? | .28 | **.79** | -.28 | .22 | **.85** |
| 19. In a typical week you use marijuana, how much marijuana do you personally use? | .36 | **.80** | -.20 | .18 | **.62** |

| | | | | | |
|---|---|---|---|---|---|
| 20. On a typical day you use marijuana, how many sessions do you have? | .34 | **.92** | -.29 | .13 | .38 |
| 22. In a typical session you use cannabis concentrates, how many hits do you personally take? | .16 | .05 | -.10 | **.92** | .11 |
| 23. On a typical day you use cannabis concentrates, how many hits do you personally take? | .07 | .12 | -.10 | **.85** | .10 |
| 24. How many hits of cannabis concentrates did you personally take yesterday? | .36 | .10 | -.09 | **.72** | .21 |
| 25. On a typical day you use cannabis concentrates, how many sessions do you have? | .13 | .12 | -.04 | **.65** | .13 |
| 27. When you eat edibles how many milligrams of THC do you personally ingest in a typical session? | -.27 | .34 | -.21 | .14 | **.58** |
| 30. How old were you when you FIRST tried cannabis? | -.29 | -.35 | **.72** | -.14 | -.23 |
| 31b. How old were you when you FIRST STARTED using cannabis regularly (2 or more times/month)? | .03 | -.42 | **.88** | -.09 | -.19 |
| 31ci. How old were you when you FIRST STARTED using cannabis on a daily or near daily basis? | .23 | -.13 | **.79** | -.05 | -.01 |
| 32. Which of the following best captures the average frequency that you used cannabis before the age of 16? | -.05 | -.14 | **.84** | -.12 | -.12 |

*Note.* Bold text indicates that the item loads onto that factor. Factor loadings ≥ .45 loaded onto the factor.

Table 5. *Univariate Linear Regression of DSM-5 Cannabis Use Disorder Symptoms on the Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Use Inventory Principal Components and Principal Axis Factoring Factors*

| | Cannabis Consequences | | | Cannabis Use Disorder Symptoms | | |
|---|---|---|---|---|---|---|
| | ß | $r^2$ | *p* | ß | $r^2$ | *p* |
| PCA Component | | | | | | |
| Frequency | .38 | .14 | <.001 | .39 | .15 | <.001 |
| Typicality of Use | .42 | .17 | <.001 | .43 | .18 | <.001 |
| Concentrates | .18 | .03 | .001 | .16 | .03 | .003 |
| Age of Onset | -.26 | .07 | <.001 | -.16 | .03 | < .001 |
| PAF Factor | | | | | | |
| Frequency | .39 | .16 | <.001 | .40 | .16 | <.001 |
| Typicality of Use | .44 | .20 | <.001 | .45 | .20 | <.001 |
| Concentrates | .20 | .04 | .002 | .17 | .03 | .01 |
| Age of Onset | -.37 | .14 | <.001 | -.27 | .07 | <.001 |
| Quantity | .48 | .23 | <.001 | .52 | .27 | <.001 |

*Note.* PCA = principal components analysis, PAF = principal axis factoring.

Table 6. *Correlations between DFAQ-CU Components and Measures of Alcohol and Cannabis*

| | 1. | 2. | 3. | 4. | 5. | 6. | 7. | 8. | 9. | 10. | 11. | 12. | 13. | 14. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. DFAQ-CU Frequency | - | | | | | | | | | | | | | |
| 2. DFAQ-CU Age of Onset | **-.16** | - | | | | | | | | | | | | |
| 3. DFAQ-CU Concentrates | **.38** | **-.21** | - | | | | | | | | | | | |
| 4. DFAQ-CU Typicality of Use | **.90** | **-.25** | **.40** | - | | | | | | | | | | |
| 5. Past Month Cannabis Frequency | **.83** | **-.11** | **.37** | **.67** | - | | | | | | | | | |
| 6. Average Weekday Cannabis Quantity | **.33** | -.06 | **.17** | **.37** | **.24** | - | | | | | | | | |
| 7. Average Weekend Cannabis Quantity | **.36** | .00 | **.33** | **.51** | **.29** | **.75** | - | | | | | | | |
| 8. Cannabis Consequences | **.34** | -.07 | **.13** | **.37** | **.36** | .04 | .11 | - | | | | | | |
| 9. CUD Symptoms | **.34** | **-.10** | **.15** | **.37** | **.34** | .12 | **.23** | **.67** | - | | | | | |
| 10. Past-year Alcohol Frequency | .02 | .04 | .06 | .00 | .03 | .04 | .09 | **-.19** | **.15** | - | | | | |
| 11. Past-year Alcohol Binges | **-.11** | .07 | -.11 | **-.14** | -.07 | .00 | -.07 | **-.21** | **.20** | **.60** | - | | | |
| 12. Past-Two Week Alcohol Frequency | -.09 | -.02 | -.01 | **-.12** | -.04 | -.04 | -.02 | **-.16** | **.19** | **.60** | **.50** | - | | |
| 13. Past-Two Week Alcohol Binges | **-.15** | **.10** | -.09 | **-.19** | -.07 | -.13 | -.13 | **-.16** | **.23** | **.40** | **.55** | **.60** | - | |
| 14. AUD Symptoms | .01 | -.01 | .07 | .05 | -.02 | -.07 | .14 | **.32** | **.39** | **.31** | **.30** | **.29** | **.28** | - |

*Note.* DFAQ-CU = daily sessions, frequency, age of onset, and cannabis use quantity questionnaire; CUD = cannabis use disorder; AUD = alcohol use disorder; weekday = Monday – Thursday; Weekend = Friday – Sunday. Bold indicates significance at $p < .05$.

## DISCUSSION

The present study aimed to evaluate the structure of the DFAQ-CU using reflective and formative modeling approaches. Results of the current analyses suggest that 1) reflective and formative modeling result in different structures, highlighting the importance of selecting theoretically appropriate modeling techniques (e.g., Borsboom et al., 2003; Rhemtulla et al., 2020); 2) modeling formative items as reflective can result in overestimations of relations between constructs and outcomes; and 3) components of the DFAQ-CU demonstrate evidence of convergent and discriminant validity with existing measures of cannabis and alcohol use.

Use of PCA resulted in four components. The Typicality of Use component assesses an individual's regular patterns of use; the Frequency component assesses the number of uses in a given time frame; the Age of Onset component characterizes age of first use and first regular use; and the Concentrates component measures the use of cannabis concentrates. Conceptually, these components capture different facets of cannabis use and use patterns. The Age of Onset and Concentrate components are comparable to Cuttler and Spradlin's (2017) solution. However, the remaining components, though similar in name (e.g., Frequency), are comprised of different core items. In the PCA solution, the Typicality of Use component accounts for an individual's typical pattern of use while the Frequency component accounts for frequency in a given timeframe. These two components are distinct in that the Frequency component could capture differences in recent use (e.g., decreased use in the past week due to studying for an exam). Further, items of the Frequency component are primarily Likert-like items while the Typicality of Use component is comprised primarily of open-response items, which could partially explain relations between items of these components. Of note, the Typicality of Use and Frequency components have a correlation of .90, demonstrating a meaningful amount of overlap. Overall, modeling the core items as formative resulted in a structure unique from the original reflective solution (Cuttler & Spradlin, 2017). This finding corroborates extant literature highlighting the importance of selecting theoretically appropriate models for evaluating the structure of assessment tools (e.g., Borsboom et al., 2003; Rhemtulla et al., 2020) and the development of practical constructs for outcome studies.

Though conceptual arguments suggest that the DFAQ-CU should be modeled as formative, the present study also aimed to replicate the original factor structure of the DFAQ-CU using reflective modeling (i.e., PAF) which resulted in a five-factor solution with a high degree of cross-loading, (i.e., 8 of 22 items) suggesting that reflective strategies does not result in simple structure and that there may be multicollinearity between factors. Only the Concentrates and Age of Onset factors resulted in items with no cross-loading. Ultimately, this pattern of findings suggests that when modeled as reflective, there may be limited distinguishability between items targeting frequency, quantity, and typical patterns of use. Notably, the original DFAQ-CU found correlations between factors ranging from -.16 to .52 (Cuttler & Spradlin, 2017 p. 8), whereas we found much higher correlations among factors, up to .95. High correlations between factors further suggest that the factors originating from PAF may not be capturing distinct facets of use. Though some factors from Cuttler and Spradlin's work have similar names and are comprised of identical manifest variables compared to the factors and components of the current study (e.g., Age of Onset), these factors resulted in different relations with other factors and cannabis use outcomes. This is consistent with extant literature highlighting that latent variables thought to be similar across studies can result in discrepant relations with outcomes (e.g., Levin-Aspenson et al., 2020). Notably, fit indices derived using CFAs of the present PAF model and using Cuttler and Spradlin's original structure resulted in poor fit to the data, further highlighting that reflective models may not be appropriate for this measure. It is worth noting here that PCAs are data transformations and are not subject to fit indices such as CFI and RMSEA. The poor fit of the CFA models add support to the need to reevaluate the DFAQ-CU, but do not suggest that the PCA "fits" the data better; rather, the data is more appropriate for formative models.

Using PCA, the Typicality of Use and Frequency components yielded medium size associations with cannabis use consequences and CUD symptoms. The Concentrates and Age of

Onset components yielded small effects. Overall, findings suggest that regularity of use and typical use behaviors are the strongest indicators of both cannabis-related consequences and CUD symptoms. This finding mirrors extant literature that reports strong relations between frequency of use and cannabis problems (e.g., Pearson, 2019), which may be because more frequent/regular use likely results in more opportunities to incur negative consequences because of use. Importantly, in line with Rhemtulla et al. (2020), there were higher correlations among PAF factors compared to PCA components, and regressions between PAF factors and outcomes resulted in larger effect sizes than models examining PCA components and outcomes. With the rationale described by Rhemtulla et al. (2020) in mind, these results indicate inflated estimates when using reflective modeling with formative variables. Said another way, using reflective models when formative models are more conceptually appropriate may significantly bias findings by over-estimating the relations between variables and outcomes of interest. This risk of estimate inflation has important clinical implications for cannabis use and psychopathology more broadly. If clinical decision making is partially grounded on self-report assessment responses that were modeled incorrectly, we may be making evaluations of risk or treatment selection based on inflated effect sizes. For example, using the DFAQ-CU modeled as reflective, Concentrates and Age of Onset resulted in doubling of their effect sizes compared to the PCA. If this effect were multiplied over several studies (e.g., using meta-analysis), researchers and clinicians may conclude that age of first use is a strong indicator of risk for CUD and this could result in potentially inappropriate treatment referrals based on an early age of first use regardless of current pattern or use of resources being used for intervention development specifically for those with earlier age of onset.

Broadly, the components of the DFAQ-CU demonstrated evidence of convergent and discriminant validity with measures of cannabis and alcohol use. The DFAQ-CU components correlated most highly with other measures of cannabis frequency and cannabis outcomes as compared to alcohol use and symptoms. In particular, the Frequency and Typicality of Use components evinced moderate-to-large correlations with cannabis use measures but negligible-to-small correlations with alcohol measures. The Concentrates component had small-to-moderate correlations with cannabis outcomes and negligible relations to alcohol measures. The exception was the Age of Onset component which elicited small correlations with cannabis consequences and CUD symptoms as well as alcohol binge frequency. It is likely that this pattern occurred as individuals with an earlier age of cannabis use onset are also at increased risk of heavy alcohol consumption (Nelson et al., 2015; Schauer et al., 2020). Additionally, all four components were moderately-to-highly correlated with measures of cannabis consequences and CUD symptoms, suggesting predictive utility of the DFAQ-CU.

Overall, findings of the present study indicate that modeling strategies result in differing structures. The present sample was comprised of college students in a location without legalized cannabis, whereas Cuttler and Spradlin's sample was assessed in a state with legalized medicinal and recreational cannabis. Although both samples were predominately White and female, the present sample had more Hispanic/Latinx students whereas the Cuttler & Spradlin sample had more Asian and Black participants. These contextual and demographic factors may have played a role in differences in factor/component structures and correlations between studies. However, given the arguments in favor of formative modeling strategies for the type of constructs most relevant to cannabis use, measures aiming to understand cannabis use behaviors should carefully consider modeling approaches during measure development.

### *Limitations and Future Directions*

Several limitations of the proposed study warrant discussion. The DFAQ-CU asks participants about their primary form and forms used at least 25% of the time, however, it may be important to assess any lifetime use of cannabis forms in addition to regularly used forms. Additionally, although the DFAQ-CU aimed to mitigate several issues with earlier cannabis assessments, it still lacks core items assessing potency and other facets of use. Further, the use of skip logic contributed to missing data related to concentrates and age of onset, which necessitated the use of component means when examining correlations and outcomes. However, in PCA modeling, components scores are typically derived by multiplying an individual's score on each item by the corresponding eigenvector and summing these values to create a singular score for each component, which was not possible in this case. Globally, this points to a larger weakness in the DFAQ-CU as a whole. Namely, as a result, true component scores for the DFAQ-CU cannot be calculated without bias, necessitating that "components" be calculated as the means of the individual items within a component. Additionally, the 95% confidence interval was used for parallel analysis to determine factor and component retention. Though this approach is considered strong, it should be noted that using the mean eigenvalue as opposed to the 95% confidence interval is best for highly correlated factors whereas the 95% confidence interval is best for factors and components with 6 or more items (Crawford et al., 2010). The present structure resulted in moderate-to-high correlations between components and factors and 4 to 10 items per component or factor. Lastly, despite anonymity of participant responses cannabis possession was illegal in Texas at the time of data collection, so participants may have underreported their use. In response to the outcomes of this study and considering the limitations, several future directions for research are offered.

First, the DFAQ-CU will require further replication of its formative structure and, ideally, modification of skip logic to allow for more appropriate calculation of PCA component scores. Importantly, the present work offers a theoretical argument for use of a formative approach. However, there are analytic techniques such as tetrad confirmatory analyses (Bollen & Ting, 1993) that could empirically indicate model selection. Presently, packages for use of these methods are not widely available but as access to this methodology increases, empirical selection of formative compared to reflective modeling is needed. Second, the DFAQ-CU assesses several methods of administration (e.g., loose leaf, concentrates, edibles). It is relevant to consider method of administration as quantity estimates also differ as a function of method (e.g., Mariani et al., 2011), and even moderate-to-heavy users of cannabis have difficulty estimating the quantity of their use (Prince et al., 2018). As such, work relying on self-reported cannabis quantity should be replicated using alternative measurement techniques (e.g., weighing individuals' self-made cannabis products; Prince et al., 2018) before drawing conclusions on relations between quantity of use and outcomes.

Third, understanding how the components of the DFAQ-CU relate to outcomes (e.g., consequences, CUD symptoms) across different timeframes and contexts would yield interesting findings. For example, future works should assess if strength of relations between components and outcomes differ by college attendance status. Additionally, item response analyses to understand which items in particular are most apt at predicting risk could help to create a brief screening measure that could be applied in various settings (e.g., primary care) and reduce potential redundancy in items. Future work should also consider not only the number of use sessions per day, but the timing of these sessions, which can impact cannabis-related problems (e.g., Babson et al., 2017, Bolla et al., 2008; Drazdowski et al., 2019; Earleywine et al., 2016). Finally, measurement of cannabis use is lacking in its ability to assess potency of cannabis products, which is hampered due to wide variability across measurement methods, strains, and product stability (Jikomes & Zoob, 2018). Recent innovations such as the Purpl Pro have increased ability to assess THC content (Trull et al., 2022) and could improve our understanding of the role of THC concentration in predicting subsequent outcomes.

More broadly, the present findings lend support to the importance of model selection and the potential risks of misdisattenuation. These issues reach beyond the DFAQ-CU and may impact any survey-based research. Careful evaluation of existing measures is warranted to determine if the model structure and scoring is appropriate for items and if not, replication of existing research is needed to determine if there is evidence of inflated estimates across measures and associated outcomes.

### *Conclusions*

Overall, this work suggests that disparate modeling techniques can result in different solutions. These discrepancies may have substantial implications for the constructs being evaluated and the relevance of these constructs for outcomes of societal and clinical interest. As such, model selection should be carefully considered during measure development and in outcome studies. Regarding the DFAQ-CU, the two modeling approaches failed to yield simple structure using two modeling approaches. Replications of the DFAQ-CU may want to considering reducing potentially redundant items to minimize overlap between components. Further, the use of skip logic, particularly in relation to concentrate use and age of onset, necessitated the use of averages to create component scores as opposed to use of eigenvector multiplication. Presently, the flaws inherent in the assessment (e.g., skip logic) in addition to a potential lack of simple structure for both modeling approaches suggests that the DFAQ-CU may not be suitable for use in its current form. However, if the DFAQ-CU were modified to eliminate skip logic and potentially redundant items, use of formative modeling on an updated version of the measure could be appropriate and useful.

## REFERENCES


American Psychiatric Association. (2013). *Diagnostic and Statistical Manual of Mental Disorders* (5th ed.). https://doi.org/10.1176/appi.books.9780890425596

Azagba, S., & Asbridge, M. (2019). Age of first use, current marijuana use and driving after use among Canadian high school students. *Addictive behaviors*, *90*, 329-333. https://doi.org/10.1016/j.addbeh.2018.11.042.

Babson, K. A., Sottile, J., & Morabito, D. (2017). Cannabis, cannabinoids, and sleep: a review of the literature. *Current psychiatry reports*, *19*(4), 23-34. https://doi.org/10.1007/s11920-017-0775-9

Bartlett, M. S. (1950). Tests of significance in factor analysis. *British Journal of statistical psychology*, *3*(2), 77-85.

Bashford, J., Flett, R., & Copeland, J. (2010). The Cannabis Use Problems Identification Test (CUPIT): Development, reliability, concurrent and predictive validity among adolescents and adults. *Addiction*, *105*(4), 615-625. https://doi.org/10.1111/j.1360-0443.2009.02859.x

Bolla, K. I., Lesage, S. R., Gamaldo, C. E., Neubauer, D. N., Funderburk, F. R., Cadet, J. L., David, P. M., Verdejo-Garcia, A., & Benbrook, A. R. (2008). Sleep disturbance in heavy marijuana users. *Sleep*, *31*(6), 901–908. https://doi.org/10.1093/sleep/31.6.901

Bollen, K. A. (1989). *Structural equations with latent variables* (Vol. 210). John Wiley & Sons.

Bollen, K. A., & Ting, K. F. (1993). Confirmatory tetrad analysis. *Sociological Methodology*, 147-175. https://doi.org/10.2307/271009

Borsboom, D. (2006). The attack of the psychometricians. *Psychometrika*, *71*(3), 425-440. https://doi.org/10.1007/s11336-006-1447-6

Borsboom, D., Mellenbergh, G. J., & Van Heerden, J. (2003). The theoretical status of latent variables. *Psychological review*, *110*(2), 203-219. https://doi.org/10.1037/0033-295X.110.2.203

Borsboom, D., Mellenbergh, G. J., & Van Heerden, J. (2004). The concept of validity. *Psychological Review*, *111*(4), 1061-1071. https://doi.org/10.1037/0033-295X.111.4.1061

Callaghan, R. C., Sanches, M., & Kish, S. J. (2020). Quantity and frequency of cannabis use in relation to cannabis-use disorder and cannabis-related problems. *Drug and Alcohol Dependence*, *217*, 108271. https://doi.org/10.1016/j.drugalcdep.2020.108271

Carliner, H., Brown, Q. L., Sarvet, A. L., & Hasin, D. S. (2017). Cannabis use, attitudes, and legal status in the US: a review. *Preventive Medicine*, *104*, 13-23. https://doi.org/10.1016/j.ypmed.2017.07.008

Cerdá, M., Wall, M., Keyes, K. M., Galea, S., & Hasin, D. (2012). Medical marijuana laws in 50 states: investigating the relationship between state legalization of medical marijuana and marijuana use, abuse and dependence. *Drug and Alcohol Dependence*, *120*(1-3), 22-27. https://doi.org/10.1016/j.drugalcdep.2011.06.011

Coltman, T., Devinney, T. M., Midgley, D. F., & Venaik, S. (2008). Formative versus reflective measurement models: Two applications of formative measurement. *Journal of Business*

*Research*, *61*(12), 1250-1262. https://doi.org/10.1016/j.jbusres.2008.01.013

Crawford, A. V., Green, S. B., Levy, R., Lo, W. J., Scott, L., Svetina, D., & Thompson, M. S. (2010). Evaluation of parallel analysis methods for determining the number of factors. Educational and Psychological Measurement, 70(6), 885-901. https://doi.org/10.1177/0013164410379332

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3), 297-334. https://doi.org/10.1007/BF02310555

Cuttler, C., & Spradlin, A. (2017). Measuring cannabis consumption: Psychometric properties of the Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Use Inventory (DFAQ-CU). *PloS One*, *12*(5), 1-14 e0178194. https://doi.org/10.1371/journal.pone.0178194

Daniulaityte, R., Nahhas, R. W., Wijeratne, S., Carlson, R. G., Lamy, F. R., Martins, S. S., ... & Sheth, A. (2015). "Time for dabs": Analyzing Twitter data on marijuana concentrates across the US. *Drug and Alcohol Dependence*, *155*, 307-311. https://doi.org/10.1016/j.drugalcdep.2015.07.1199

De Winter, J. C., & Dodou, D. (2012). Factor recovery by principal axis factoring and maximum likelihood factor analysis as a function of factor pattern and sample size. *Journal of Applied Statistics*, *39*(4), 695-710. https://doi.org/10.1080/02664763.2011.610445

Dien, J. (2010). Evaluating two-step PCA of ERP data with geomin, infomax, oblimin, promax, and varimax rotations. *Psychophysiology*, *47*(1), 170-183. https://doi.org/10.1111/j.1469-8986.2009.00885.x

Dierker, L., Braymiller, J., Rose, J., Goodwin, R., & Selya, A. (2018). Nicotine dependence predicts cannabis use disorder symptoms among adolescents and young adults. *Drug and Alcohol Dependence*, *187*, 212-220. https://doi.org/10.1016/j.drugalcdep.2018.02.037Drazdowski, T. K., Kliewer, W. L., & Marzell, M. (2019). College students' using marijuana to sleep relates to frequency, problematic use, and sleep problems. *Journal of American College Health*, 1-10. https://doi.org/10.1080/07448481.2019.1656634

Earleywine, M., Luba, R., Slavin, M. N., Farmer, S., & Loflin, M. (2016). Don't wake and bake: morning use predicts cannabis problems. *Addiction Research & Theory*, *24*(5), 426-430. https://doi.org/10.1080/16066359.2016.1177027

Fried, E. I. (2020). Theories and models: What they are, what they are for, and what they are about. *Psychological Inquiry*, *31*(4), 336-344. https://doi.org/10.1080/1047840X.2020.1854011

Gallup. (2021, November 20). *Support for legal marijuana holds at record high of 68%*. Gallup.com. Retrieved April 11, 2023, from https://news.gallup.com/poll/356939/support-legal-marijuana-holds-record-high.aspx

Gette, J. A., Gissandaner, T. D., Littlefield, A. K., Simmons, C. S., & Schmidt, A. T. (2022). Modeling the adverse childhood experiences questionnaire–international version. *Child Maltreatment*, *27*(4), 527-538. https://doi.org/10.1177/1077559521104312

Glorfeld, L. W. (1995). An improvement on Horn's parallel analysis methodology for selecting the correct number of factors to retain. *Educational and Psychological Measurement*, 55(3), 377-393. https://doi.org/10.1177/0013164495055003002

Hall, W. (2009). The adverse health effects of cannabis use: what are they, and what are their implications for policy?. *International Journal of Drug Policy*, *20*(6), 458-466. https://doi.org/10.1016/j.drugpo.2009.02.013

Hancock, G. R., & Mueller, R. O. (2001). Rethinking construct reliability within latent variable systems. *Structural Equation Modeling: Present and Future*, 195-216.

Hasin, D. S., Kerridge, B. T., Saha, T. D., Huang, B., Pickering, R., Smith, S. M., ... & Grant, B. F. (2016). Prevalence and correlates of DSM-5 cannabis use disorder, 2012-2013: Findings from the National Epidemiologic Survey on Alcohol and Related Conditions–III. *American Journal of Psychiatry*, *173*(6), 588-599. https://doi.org/10.1176/appi.ajp.2015.15070907

Hasin, D. S., Wall, M., Keyes, K. M., Cerdá, M., Schulenberg, J., O'Malley, P. M., ... & Feng, T. (2015). Medical marijuana laws and adolescent marijuana use in the USA from

1991 to 2014: results from annual, repeated cross-sectional surveys. *The Lancet Psychiatry*, *2*(7), 601-608. https://doi.org/10.1016/S2215-0366(15)00217-5

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, *30*(2), 179-185. https://doi.org/10.1007/BF02289447

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1-55. https://doi.org/10.1080/10705519909540118

Hunt, P. E., & Miles, J. (2015). The impact of legalizing and regulating weed: issues with study design and emerging findings in the USA. In *Non-medical and Illicit Use of Psychoactive Drugs* (pp. 173-198). Springer, Cham.

IBM Corp. Released 2017. IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp.

Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, *47*(1), 5-86. DOI: 10.1257/jel.47.1.5

Jikomes, N., & Zoorob, M. (2018). The cannabinoid content of legal cannabis in Washington state varies systematically across testing facilities and popular consumer products. *Scientific reports*, *8*(1), 1-15. https://doi.org/10.1038/s41598-018-22755-2

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, *39*(1), 31-36. https://doi.org/10.1007/BF02291575

Kite, M. E., & Whitley, B. E. (2018). Factor Analysis, Path Analysis, and Structural Equation Modeling. In *Principles of Research in Behavioral Science* (pp. 466-495). Routledge.

Kline, P. (2013). *Handbook of psychological testing*. Routledge.

Levine, A., Clemenza, K., Rynn, M., & Lieberman, J. (2017). Evidence for the risks and consequences of adolescent cannabis exposure. *Journal of the American Academy of Child & Adolescent Psychiatry*, *56*(3), 214-225. https://doi.org/10.1016/j.jaac.2016.12.014

Levin-Aspenson, H. F., Watson, D., Clark, L. A., & Zimmerman, M. (2020). What is the general factor of psychopathology? Consistency of the p factor across samples. *Assessment*, 1073191120954921. https://doi.org/10.1177/1073191120954921

López-Pelayo, H., Campeny, E., Oliveras, C., Rehm, J., Manthey, J., Gual, A., & Balcells-Olivero, M. D. L. M. (2021). Early, Chronic, and Acute Cannabis Exposure and Their Relationship With Cognitive and Behavioral Harms. *Frontiers in Psychiatry*, *12*, 1-15. https://doi.org/10.3389/fpsyt.2021.643556

Lovell, M. E., Akhurst, J., Padgett, C., Garry, M. I., & Matthews, A. (2020). Cognitive outcomes associated with long-term, regular, recreational cannabis use in adults: A meta-analysis. *Experimental and Clinical Psychopharmacology*, *28*(4), 471-494. https://doi.org/10.1037/pha0000326

Mariani, J. J., Brooks, D., Haney, M., & Levin, F. R. (2011). Quantification and comparison of marijuana smoking practices: Blunts, joints, and pipes. *Drug and Alcohol Dependence*, *113*(2-3), 249-251. https://doi.org/10.1016/j.drugalcdep.2010.08.008

McDonald, R. P. (1999). *Test theory: A unified treatment*. Mahwah, NJ: L. Erlbaum Associates.

Meda, S. A., Gueorguieva, R. V., Pittman, B., Rosen, R. R., Aslanzadeh, F., Tennen, H., ... & Pearlson, G. D. (2017). Longitudinal influence of alcohol and marijuana use on academic performance in college students. *PLoS One*, *12*(3), e0172213. https://doi.org/10.1371/journal.pone.0172213

Muthén, L.K. and Muthén, B.O. (1998-2017). Mplus User's Guide. Eighth Edition. Los Angeles, CA: Muthén & Muthén.

National Institute on Alcohol Abuse and Alcoholism. Recommended Alcohol Questions. (2004,

February 5). Retrieved February 07, 2017, from https://www.niaaa.nih.gov /research/ guidelines-and-resources/recommended-alcohol-questions

Nelson, S. E., Van Ryzin, M. J., & Dishion, T. J. (2015). Alcohol, marijuana, and tobacco use trajectories from age 12 to 24 years: Demographic correlates and young adult substance use problems. *Development and psychopathology*, *27*(1), 253-277. doi:10.1017/S0954579414000650

Patrick, M. E., Schulenberg, J. E., Miech, R. A., Johnston, L. D., O'Malley, P. M., & Bachman, J. G. (2022). Monitoring the Future Panel Study annual report: National data on substance use among adults ages 19 to 60, 1976-2021 (PDF). Monitoring the Future Monograph Series. Ann Arbor: Institute for Social Research, The University of Michigan.

Pearson, M. R. (2019). A meta-analytic investigation of the associations between cannabis use and cannabis-related negative consequences. *Psychology of Addictive Behaviors*, *33*(3), 190-196. https://doi.org/10.1037/adb0000452

Pearson, M. R., Liese, B. S., Dvorak, R. D., & Marijuana Outcomes Study Team. (2017). College student marijuana involvement: perceptions, use, and consequences across 11 college campuses. *Addictive Behaviors, 66*, 83-89. https://doi.org/10.1016/j.addbeh.2016.10.019

Phillips, K. T., Phillips, M. M., Lalonde, T. L., & Tormohlen, K. N. (2015). Marijuana use, craving, and academic motivation and performance among college students: An in-the-moment study. *Addictive Behaviors*, *47*, 42–47. http://doi.org/10.1016/j.addbeh.2015.03.020

Prince, M. A., Conner, B. T., & Pearson, M. R. (2018). Quantifying cannabis: A field study of marijuana quantity estimation. *Psychology of Addictive Behaviors*, *32*(4), 426-433. https://doi.org/10.1037/adb0000370

Qualtrics, L. L. C. (2015). Qualtrics [software].

R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

Revelle, W. (2020). *How to use the psych package for factor analysis and data reduction.* Retrieved from http://personality-project.org/r/psych/HowTo/factor.pdf

Rhemtulla, M., van Bork, R., & Borsboom, D. (2020). Worse than measurement error: Consequences of inappropriate latent variable measurement models. *Psychological Methods, 25*(1), 30-45. https://doi.org/10.1037/met0000220

Richmond-Rakerd, L. S., Slutske, W. S., Lynskey, M. T., Agrawal, A., Madden, P. A., Bucholz, K. K., ... & Martin, N. G. (2016). Age at first use and later substance use disorder: Shared genetic and environmental pathways for nicotine, alcohol, and cannabis. *Journal of Abnormal Psychology*, *125*(7), 946-959. https://doi.org/10.1037/abn0000191

Rioux, C., Castellanos-Ryan, N., Parent, S., Vitaro, F., Tremblay, R. E., & Séguin, J. R. (2018). Age of cannabis use onset and adult drug abuse symptoms: a prospective study of common risk factors and indirect effects. *The Canadian Journal of Psychiatry*, *63*(7), 457-464. https://doi.org/10.1177/0706743718760289

Roditis, M. L., Delucchi, K., Chang, A., & Halpern-Felsher, B. (2016). Perceptions of social norms and exposure to pro-marijuana messages are associated with adolescent marijuana use. *Preventive Medicine*, *93*, 171-176. https://doi.org/10.1016/j.ypmed.2016.10.013

Rodriguez, A., Reise, S. P., & Haviland, M. G. (2016). Applying bifactor statistical indices in the evaluation of psychological measures. *Journal of Personality Assessment, 98*(3), 223-237. https://doi.org/10.1080/00223891.2015.1089249

Russell, C., Rueda, S., Room, R., Tyndall, M., & Fischer, B. (2018). Routes of administration for cannabis use–basic prevalence and related health outcomes: A scoping review and synthesis. *International Journal of Drug Policy*, *52*, 87-96. https://doi.org/10.1016/j.drugpo.2017.11.008

Schultz, N. R., Bassett, D. T., Messina, B. G., & Correia, C. J. (2019). Evaluation of the psychometric properties of the cannabis use disorders identification test-revised among college students. *Addictive Behaviors*, *95*, 11-15. https://doi.org/10.1016/j.addbeh.2019.02.016

Simons, J. S., Dvorak, R. D., Merrill, J. E., & Read, J. P. (2012). Dimensions and severity of marijuana consequences: Development and validation of the Marijuana Consequences Questionnaire (MACQ). *Addictive Behaviors*, *37*(5), 613-621. https://doi.org/10.1016/j.addbeh.2012.01.008

Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2007). *Using multivariate statistics* (Vol. 5, pp. 481-498). Boston, MA: Pearson.

Taylor, R. D., Poulton, R., Moffitt, E. T., Ramankutty, P., & Sears, R.M. (2000). The respiratory effects of cannabis dependence in young adults. *Addiction, 95*, 1669-1677. https://doi.org/10.1046/j.1360-0443.2000.951116697.x

Tomko, R. L., Baker, N. L., McClure, E. A., Sonne, S. C., McRae-Clark, A. L., Sherman, B. J., & Gray, K. M. (2018). Incremental validity of estimated cannabis grams as a predictor of problems and cannabinoid biomarkers: Evidence from a clinical trial. *Drug and Alcohol Dependence*, *182*, 1-7. https://doi.org/10.1016/j.drugalcdep.2017.09.035

Trull, T. J., Freeman, L. K., Fleming, M. N., Vebares, T. J., & Wycoff, A. M. (2022). Using ecological momentary assessment and a portable device to quantify standard tetrahydrocannabinol units for cannabis flower smoking. *Addiction 117*(8) 2351-2358. https://doi.org/10.1111/add.15872

Van Ginkel, J. R., Kroonenberg, P. M., & Kiers, H. A. (2014). Missing data in principal component analysis of questionnaire data: a comparison of methods. *Journal of Statistical Computation and Simulation*, *84*(11), 2298-2315. https://doi.org/10.1080/00949655.2013.788654

Velicer, W. F., Eaton, C. A., & Fava, J. L. (2000). Construct explication through factor or component analysis: A review and evaluation of alternative procedures for determining the number of factors or components. In *Problems and solutions in human assessment* (pp. 41-71). Springer, Boston, MA.

Velicer, W. F., & Jackson, D. N. (1990). Component analysis versus common factor analysis: Some issues in selecting an appropriate procedure. *Multivariate Behavioral Research*, *25*(1), 1-28. https://doi.org/10.1207/s15327906mbr2501_1

Wall, M. M., Mauro, C., Hasin, D. S., Keyes, K. M., Cerda, M., Martins, S. S., & Feng, T. (2016). Prevalence of marijuana use does not differentially increase among youth after states pass medical marijuana laws: commentary on and reanalysis of US National Survey on Drug Use in Households data 2002–2011. *International Journal of Drug Policy*, *29*, 9-13. https://doi.org/10.1016/j.drugpo.2016.01.015

Wen, H., Hockenberry, J. M., & Cummings, J. R. (2015). The effect of medical marijuana laws on adolescent and adult use of marijuana, alcohol, and other substances. *Journal of Health Economics*, *42*, 64-80. https://doi.org/10.1016/j.jhealeco.2015.03.007

Zeisser, C., Thompson, K., Stockwell, T., Duff, C., Chow, C., Vallance, K., ... & Lucas, P. (2012). A 'standard joint'? The role of quantity in predicting cannabis-related problems. *Addiction Research & Theory*, *20*(1), 82-92. https://doi.org/10.3109/16066359.2011.569101

**Funding and Acknowledgements:** The submitted manuscript was not funded by any internal or external funding sources. The authors have no conflicts of interest to report.

Copyright: © 2023 Authors et al. This is an open access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction, provided the original author and source are credited, the original sources is not modified, and the source is not used for commercial purposes.