12-2021

Personality as a Predictor of Patterns of Substance Use

Cynthia Sergi
cmsergi@uno.edu

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A Thesis

Submitted to the Graduate Faculty of the
University of New Orleans
in partial fulfillment of the
requirements for the degree of

Master of Science
In
Psychology

By

Cynthia Sergi

B.S. University of New Orleans, 2016

December 2021

Table of Contents

List of Figures

List of Tables

Abstract

Substance use (SU) affects many people worldwide and is an important public health concern. Personality has been theorized to play a crucial role in the development and maintenance of SU. To test how personality is related to patterns of SU, a latent profile analysis was used to cluster individuals into SU classes with multinomial logistic regression used to test the relationship between personality and patterns of SU. Results suggested that polysubstance use was common, with variations in primary substance of choice among classes. As classes became more inclusive of more substances, they increased in psychopathological personality traits. Higher domains of personality traits were used to predict the classes while the least severe SU class was used as a referent. Results indicated that each domain of personality and facet level traits had an effect on the SU classes. Facet level traits are more so affected when considering levels of polysubstance use.

Keywords: patterns of substance use; personality traits and substance use; polysubstance use patterns

Chapter 1

Introduction

Substance use disorders (SUD) affect many people worldwide and there are a multitude of negative consequences of heavy substance use (SU; World Health Organization, 2004). For instance, heavy SU takes a toll on physical, mental, and intrapersonal health, as well as being a common cause of mortality (National Institute on Drug Abuse, 2017). SUDs are damaging not only to the individual, but also to family, friends, and society at large (NIDA, 2017). There is a large literature linking personality traits to heavy SU as well as SUD (McCormick, et. al, 1998; Allen, et. al, 1998). However, this literature is limited by not clearly determining if personality traits predict patterns of drug use. Understanding specific traits that contribute or predispose an individual to developing specific patterns of substance use and SUD has the potential to improve etiological and prevention models of SU and SUD.

The idea that temperament and personality traits predispose individuals to SU and SUD is not a new idea (e.g., Cloninger, Svrakic, & Przybeck, 1993; Caspi, et. al, 2014). Researchers have used a variety of different personality theories and measures to assess the relationship, such as the Schedule for Nonadaptive and Adaptive Personality (SNAP; Clark, et. al, 2014), the Temperament and Character Inventory (TCI; Milivojevic, et. al, 2012), and the NEO-Personality Inventory (NEO-PI; McCormick et al., 1998), to name a few. Complicating matters further, there are personality theories that are specific to SU and SUD (Cloninger, 1987; Eysenck, 1997; Widiger & Smith, 1994; Suh, et. al, 2008); some personality theories overlap (Calabrese, et. al, 2012); and some general conclusions concerning SU and SUD cut across perspectives. For instance, impulsivity, sensation seeking, and risk taking have been implicated as predictors of substance use (deWit, 2009; Tarter, 2002; Tarter, et. al, 2003; Evren & Bozkurt, 2016) as well as risk factors for the development of SUDs (LeBon, et. al, 2004; Dawe, Gullo, & Loxton, 2004; Gullo, Loxton, & Dawe., 2014; Nigg, et. al, 2006). Some authors argue that sensation-seeking and disinhibition are components of impulsivity. For instance, some researchers consider impulsivity as two dimensions, namely sensitivity to reward and disinhibition (rash impulsivity), both of which are related to high approach in risky situations (Gullo, et. al, 2014). Individuals who are high on impulsivity or who lack inhibitory control, often act without reflection of consequence (Colder & Chassin, 1997). Evidence links impulsive behaviors to many components of SUD, including onset, maintenance, and relapse (Evren, et al., 2016). Novelty seeking or sensation seeking refers to an individual's tendency to seek out or pursue exciting and rewarding activities (Gullo, et al., 2014). Those low on harm-avoidance (fear or anxiety of danger or consequence) and reward dependence (attachment, social rewards) are also at an elevated risk for later SUDs (Cloninger, 1988). Furthermore, studies using the five-factor model of personality have compared individuals with SUDs to healthy controls and found that individuals with SUDs tend to be higher in neuroticism (individual differences of negative responses to threat, frustration, or loss), as well as lower in openness (willingness to explore new ideas or try new things; McCormick et al., 1998). In addition, individuals with SUDs tend to be lower on agreeableness (how cooperative or compassionate an individual is) and conscientiousness (how organized, dependable, or diligent an individual is; McCormick et al., 1998).

Reviews of the current literature have argued that specific drugs are linked to certain traits (LeBon, et al., 2004; Milivojevic, et al., 2012; Conway, et. al, 2002; Conway, et. al, 2003; Schneider, et. al, 2015). Data has supported that opioid users are higher in novelty seeking and self-transcendence (how individuals perceive themselves as part of the world), but lower in self directedness (how responsible, reliable, self-confident a person is) when compared to individuals diagnosed with alcohol use disorder and healthy control groups (Milivojevic, et al., 2012 ; Zaaijer, et. al, 2014; LeBon, et al., 2004; Cohen, et. al, 2005). In the case of alcohol use, individuals were higher on harm avoidance than the opioid users, and also higher in novelty seeking and self-transcendence when compared to healthy controls (Milivojevic, et al., 2012; LeBon, et al., 2004). Cocaine and other stimulant users tend to score higher in impulsivity when compared to healthy controls, alcohol users, and marijuana users. When compared to healthy controls, cocaine and other stimulant users were also higher in sensation seeking (Conway et al., 2002; Conway, et al., 2003; Ersche, et. al, 2010; Ersche, et. al, 2012; Ersche, et. al, 2013). Finally, the literature is mixed when considering polysubstance use (PS; Conway et al., 2002; Conway et al., 2003). Severity of use appears to play a role in certain traits being higher (novelty seeking, sensation seeking; Ball, Carroll, & Rousaville, 1994) and lower (self-directedness, self-transcendence), although even these results were varied to some degree (Wu, et. al, 2011; Conway et al., 2002; Conway et al., 2003).

Interestingly, previous studies have only compared a few substances or compared users with a specific diagnosis to healthy controls, so it is challenging to infer how differences or similarities would present when considering a variety of substances and their co-use. Currently, most studies compare arbitrary subsets of substances. For example, Milivojevic, et al.(2012) and Le Bon, et al. (2004) both compared alcohol and opioid groups to healthy controls, Conway, et al. (2003) and Wang, Wang, & Chen (2017) included alcohol, stimulants, and opiates in their research, and then in other cases, there were studies comparing users and non-users of a substance or substances (Ershe, et al. 2010; Hopwood et al., 2011). There are even studies investigating substances such as opiates (Zaaijer et al., 2014) or cocaine (Ersche et al., 2013) that compared recreational users who did not develop a SUD to those who did. In these cases, there were only specific substances considered, which omits comparing results from a wide variety of substances in the same study. Complicating matters further, individuals with rarer SUDs such as cocaine and opiate use disorder often display high levels of alcohol, tobacco, and marijuana use (Agrawal, et. al, 2007; Wu, et al., 2011). Although many studies have considered how traits were related to various substances, no research has considered traits in conjunction with patterns of SU while considering a comprehensive set of the most and least used substances. This investigation aims to ascertain if risky traits are linked to specific patterns of SU.

Personality

There are many measures of personality and many theories of personality undergird these measures. Many of the current models, such as the NEO-I five-factor model are based on nonpathological personality traits (Simms, et. al, 2010). The NEO-I measures personality using the higher order "Big-Five" factors of neuroticism, extraversion, openness, conscientiousness, and agreeableness. Although used frequently, the NEO-I does not capture pathological personality at the facet level (Wright & Simms, 2014). Most of the NEO-I maladaptive factors are included in the neuroticism domain. This is problematic given the heterogeneous nature of personality pathology. Considering pathology across all domains within a broader dimensional framework may advance the literature.

Other models have proposed measuring personality from a bottom up approach, where the lower order factors are used to determine the higher order domains. For instance, the SNAP-2 considers the three broad domains of negative affectivity, positive affectivity, and disinhibition vs. constraint by assessing trait dimensions of those domains (Vanderbleek & Clark, 2017). The higher-order factors of personality found in the SNAP are similar to Eysneck's "Big-Three" structure (Vanderbleek & Clark, 2017). The SNAP-2 is used to assess personality traits from normal to pathological (Clark & Vanderbleek, 2016) and does so by allowing the lower order traits to inform the latent personality constructs. Similar to the SNAP, the Computerized Adaptive Test of Personality Disorder (CAT-PD), which was developed by Simms, et. al (2011), also uses a dimensional approach to assess personality. The CAT-PD was designed to identify comprehensive and integrative lower and higher order personality traits of personality pathology in an efficient computerized test (Simms et. al, 2011). The CAT-PD has strong convergence with the DSM-5's section III PD model (PID-5) and through hierarchical analyses has shown the benefits of using a measure of broad dimensions to assess normative and pathological functioning (Wright & Simms, 2014). The current study will utilize the CAT-PD to test the relationship between traits and substance use patterns.

Substance Use

As mentioned previously, individuals endorsing SU and SUD symptoms are likely to be high on some traits and/or low on others when compared to healthy controls. For instance, it is likely that any SU will coincide with higher novelty/sensation seeking, impulsivity, and disinhibition. As the number of substances and level of SU increases, more extreme deviations in observed personality traits, as well as a larger number of differences is expected.

In previous large epidemiological studies, latent class analysis (LCA) has been used to assess patterns of individual SU and polysubstance use (Agrawal et.al, 2007; Smith et. al, 2011; Quek et. al, 2013). There are similarities and differences in pattern groupings among substance using individuals. For instance, Agrawal et. al (2007), found five classes of SU and SUD; no substance use (class 1), cannabis (class 2), stimulants and hallucinogens (class 3), prescription drugs (class 4), and high PS use (class 5). Quek et. al (2013) also found five classes; alcohol only (class 1), alcohol and tobacco (class 2), cannabis, ecstasy, and licit (legal) drugs (class 3), cannabis, amphetamine derivatives, and licit drugs (class 4), and sedatives and alcohol (class 5). When Smith et. al (2011) investigated SU in Great Britain, they found three classes, which consisted of a wide range polydrug use (class 1), moderate range polydrug use (class 2), and mild/no polydrug use (class 3).

Class structures suggest that there is more PS use than indicated by the class labels. In most cases, as the amount of substances increases, so does the variability in SU. For example, the labels in Agrawal et. al (2007) included certain substances, but individuals within these classes also had high or moderate probabilities of other substance use in each class. This is also true of Quek et. al (2013), with a specific example being class 5 (sedative and alcohol), which also included moderate to high probabilities of tobacco, cannabis, ecstasy, and pain killers. Therefore, it is important to recognize that labels given to classes were not fully inclusive of all SU endorsements within the classes. Furthermore, the Smith et al. (2011) study found classes of PS use that varied in severity. The pattern of findings suggests that prior research comparing specific substances on traits may be biased by ignoring substances that have a strong correlation with other substances or by creating groups of individuals with SUDs that are not reflective of patterns of SU in the overall population. Although prior work has considered patterns of drug use using LCA and other work has considered how personality is related to specific drugs, no research has considered how pathologically personality traits relate to drug use patterns when considering many of the more commonly (e.g., caffeine and alcohol) and less commonly (cocaine and opiates) used drugs. The current study will fill this critical gap in the literature.

Chapter 2

Present study

The current study used Latent Profile Analysis (LPA) to model patterns of SU across nine substances: nicotine, caffeine, alcohol, cannabis, cocaine, benzodiazepines, stimulants, opioids, and hallucinogens. The CAT-PD was then used to measure personality and to predict the classes of drug use. First, the five higher order personality factors were used to predict the classes. Second, specific facet level personality traits were then used to predict the classes. The first prediction was that LPA would reveal groups consistent with previous research of Quek, et al. (2013) and Agrawal, et. al, (2007), that show more use of licit substances (nicotine, alcohol, and caffeine), which were assumed to span across many, if not most classes. Similar to what Connor, et. al (2014) found, it was expected that groups would cluster together starting with more socially accepted substances such as alcohol, with clusters of drugs increasing, such as alcohol and marijuana, then alcohol, marijuana, and cocaine/other stimulants. As substances increase in clusters, clusters that contain opioids are expected to also include cocaine and stimulants, as well as marijuana and other illicit and licit substances. Another prediction was that as groups became more inclusive of higher PS use, severity of personality traits would increase (Ball et al. 1994; Conway et al. 2002; Conway et al. 2003). Groups containing primarily licit SU were expected to endorse less pathological personality traits, and maladaptive traits would increase as does the poly-use of illicit substances, which is consistent with high comorbidity of psychopathology (Conner, et. al, 2014) and personality disorders with SUDs (Verheul, 2001; Williams, Scalco, & Simms, 2017).

Remaining hypotheses included facet level traits from the CAT-PD which map on to the prior literature reviewed on personality and SU and SUD. Also predicted, groups of licit SU would only be high on the facet level trait of anxiousness (similar to high harm avoidance of TCI; Milivojevic, et al., 2012; LeBon, et al., 2004), which may act as a protective factor against illicit SU. In addition, it was hypothesized that LCA groups containing more illicit SU (cocaine, opioids, stimulants), would endorse more CAT-PD subscale items such as norm violation (low conscientiousness; McCormick et al., 1998) and impulsivity, including poor disinhibition (de Wit, 2009) and sensation seeking or novelty seeking (Milivojevic, et al., 2012). Specifically, facets of disinhibition (non-planfulness, irresponsibility, non-perseverance; Wright & Simms, 2014), thrill seeking (risk taking) as well as affect (affective lability, anger, anxiousness, depressiveness, mistrust, rigidity, anhedonia; Wright & Simms, 2014) were expected to be related to severity of PS use. That is, we expected larger deviations in these traits for classes with higher PS use. Higher levels of affective lability, irresponsibility, non-perseverance, non-planfulness, norm violation, and risk taking, and lower levels of anxiousness were expected to be related to classes with higher levels of PS use when compared to classes with less PS use.

Method

Participants and Procedures

Participants were recruited through Amazon's online platform known as Mechanical Turk (MTurk). Self-report questionnaires were administered via MTurk and participants were compensated $9.00 for their time (N= 1842, 57.5% were male, 74% of Caucasian race, 44% reported Bachelor level education, 25% indicated an income level of $36k-$56k). A modified timeline follow-back was used to assess SU and the Computerized Adaptive Test-Personality Disorder (CAT-PD) was used to assess personality. The current study comes from a larger project assessing the utility of a new measure of alcohol use disorder. The current study focuses on SU and personality measures taken from the larger study. This includes demographic information, a timeline follow-back to assess frequency and levels of use, as well as the CAT-PD to assess personality.

To ensure validity of the MTurk platform for this study, precautions such as “recaptchas” and grammar questions were utilized to protect against automated computer programs (“bots”). Attempts to complete the online survey would be terminated if these questions were missed. Other features, such as validity questions were also used to protect against response bias.

Substance Use measures

SU questions were asked about nicotine, caffeine, alcohol, marijuana, benzodiazepines, cocaine, stimulants, opioids, and psychedelics. A modified timeline follow back was also given to assess the quantity and frequency of SU in the past 3 months, with prompts such as “ Try to remember as accurately as you can, how much you typically drank alcohol in a week during that 90-day period. For each day of the week in the chart below, fill in the average number of drinks typically consumed on that day in the box.” Follow up questions assessed whether quantity and frequency estimates over the past three months were indicative of quantity and frequency estimates over the last year (e.g., “How typical was your drinking in the last 90 days relative to the last year?”). These items were used to create a past year quantity and frequency measure for each class of substances. The Timeline Followback (TLFB) has been found to be a highly reliable self-report measure of SU (Robinson, et. al, 2014).

Personality measure

The CAT-PD (Simms, et al. 2011) is a 246-item questionnaire used to measure personality. The CAT-PD consists of 33 facet level scales used to indicate the five latent domains of negative emotionality, detachment, antagonism, disconstraint, and psychoticism. Each facet scale has between 5 – 10 items measured on a five-point scale of 1 (very untrue of me) to 5 (very true of me). The average of participants' responses will be taken to determine each participant's score on each trait. The CAT-PD has been found to have convergent validity with the Personality Inventory for the DSM-5 (PID-5), but also taps into traits not measured by the PID-5 (Crego & Widiger, 2016) and has demonstrated a median alpha of 0.83 for the community sample and 0.85 for the patient sample (Wright & Simms, 2014).

Data analyses

Statistical analyses were completed using Mplus Version 8.3 and involved several stages. First, a latent profile analysis (LPA) was conducted on the quantity and frequency measures of SU to assess patterns of SU across all measured drugs. The number of classes to extract were determined by considering the Akaike, Bayesian, and sample size adjust Bayesian Information Criteria (AIC, BIC, ABIC; lower values being a better fit), as well as entropy, N of classes, the Lo-Mendel-Rubin (LMR) test, and the bootstrapped likelihood ratio test (BLRT) (Muthen, 2004; Lo, Mendell,& Rubin, 2001). After the number of classes to extract was determined, both higher order domain and facet level traits from the CAT-PD were used to predict the latent classes in separate analyses, using the 3-step method (Vermunt, 2010). Odds ratios were calculated for effect size (OR= 1, no effect; small OR> 1.5; moderate OR > 2.5; and large OR> 4.3).

The advantage of using the 3-step method is that it constrains classes from the LPA, so that the classes remain stable when adding the personality predictors. The three-step approach involved running a multinomial logistic regression analysis that assessed the effect of the traits on each class of drug use. The "low/no-use" class was used as the referent in all multinomial logistic regression analyses.

Results

The nine indicators used to determine substance use patterns were caffeine, alcohol, cannabis, nicotine, hallucinogens, benzodiazepines, opioids, cocaine, and stimulants, each of which had factor scores with a mean of 0 and SD of 1. An LPA was performed to assess the number of classes to be extracted based upon patterns of indicated use. Means were freely estimated within classes, but across classes the variance was constrained to be the same. Two through nine class models were estimated. More than 9 classes were not estimated due to small class proportions in the 9-class model, with the smallest being .82% of the sample size or (n = 15). Model fit statistics for the two through nine class solutions can be found in Table 1, with emphasis on the six, seven, and eight class models. The AIC, BIC, and ABIC continued to decrease in each model and the entropy only dropped to 0.998 in the 7-class and higher models, but according to both the LMR and VLMR, the 6-class model was not a significantly better model than the 5-class, just as the 5-class was not significant when comparing to the 4-class. Nonetheless, the BLRT was significant suggesting some evidence that the six-, seven-, and eight-class solutions did improve model fit. An interesting observation after extracting the seventh class was how class proportions changed compared to the 6-class model. In the 7-class model, a class with pronounced nicotine predominate/licit substance use consisting of 18% of the sample (n=331) split from the larger no/little use class which was 87% (n=1597) of the sample in the 6-class solution. In the 7-class model, the little/no use class became 69% (n=1266) of the sample after extracting the nicotine class in the seven-class solution. When extracting an additional eighth class, there was yet another interesting change, as it became apparent that there was a cocaine predominate/moderate poly-substance use class consisting of 1% of the sample (n=18). Prior to the extraction of the additional eighth class, the cocaine predominate class was included with the

Table 1
Fit Statistics for the Latent Class Analysis

Classes	AIC	BIC	ABIC	Entropy	Class Size (%)	LMR	VLMR	BLRT
2	28664.38	28818.81	28729.85	0.999	13,87	17982.51*	18221.78*	18221.78*
3	23339.61	23549.19	23428.47	0.999	4,9,87	5274.58*	5344.77*	5344.77*
4	19572.45	19837.19	19684.7	0.999	4,4,5,87	3737.43*	3787.16*	3787.16*
5	17139.3	17459.19	17274.92	0.999	2,3,4,4,87	2420.94	2453.16	2453.16*
6	14272.64	14647.69	14431.65	0.999	2,2,2,3,4,87	2848.75	2886.65	2886.65*
7	12739.28	13169.48	12921.67	0.998	2,2,2,3,4,18,69	1532.96*	1553.36*	1553.36*
8	11162.45	11647.8	11368.22	0.998	1,2,2,2,2,4,18,69	1541.91*	1562.42*	1562.42*
9	9881.85	10422.35	10111.01	0.998	.82,1,2,2,2,2,4,18,69	1283.52	1300.6	1300.6*

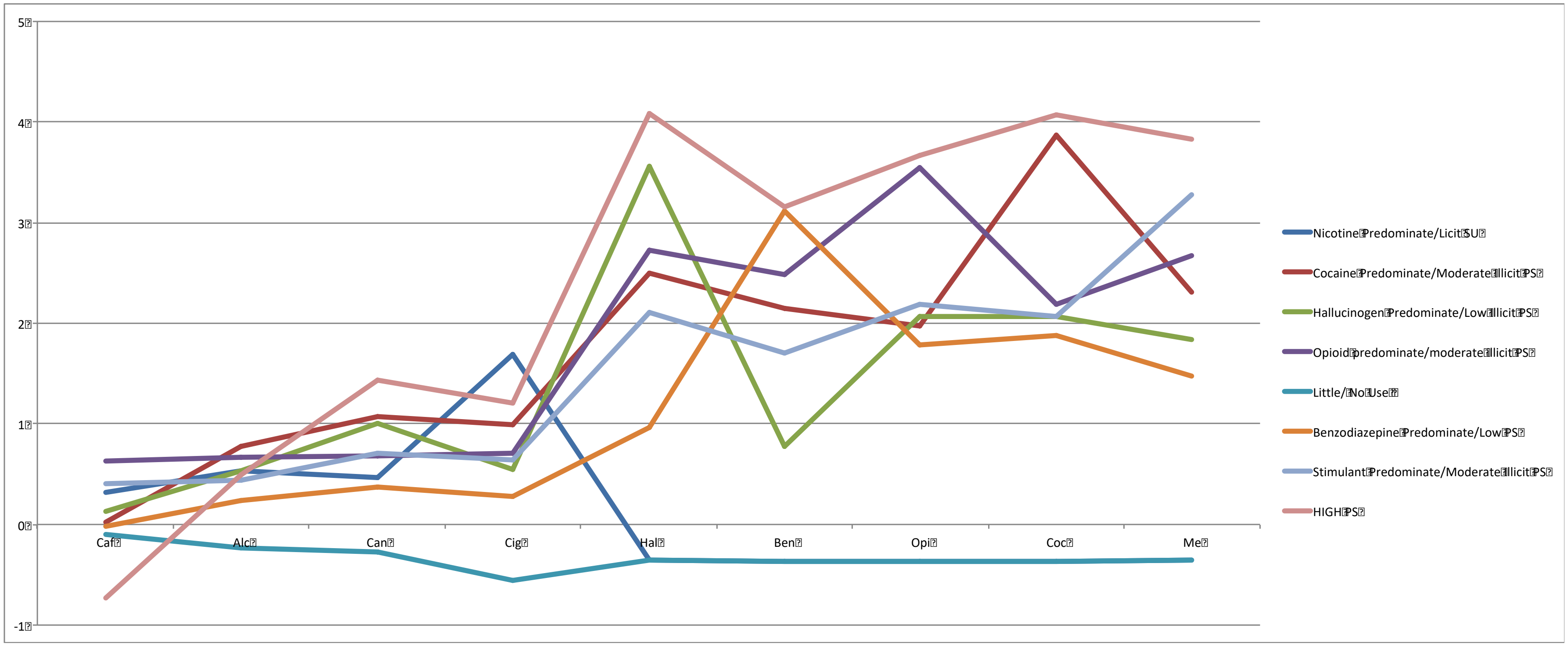
Note: AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, ABIC = Akaike's Bayesian Information Criterion, LMR = Lo-Mendell Rubin difference test, BLRT = Bayesian Likelihood Ratio Test, * = indicates statistical significance ($p < .05$).

hallucinogen predominate class, which was a hallucinogen/cocaine class. The division between the cocaine predominate and hallucinogen predominate using classes were not seen in previous analyses prior to the 8-class model and accounted for 2.5% of the sample in both the 6-class and 7-class models. The 8-class solution was chosen as the final model based on the AIC, BIC, and ABIC being lowest with appropriate class size proportions, the significance of the BLRT, and the interpretability of the model.

As the plot of the latent class structure in Figure 1 shows, there is variability in patterns of co-substance use. As expected, there was a no/little use class (n = 1266, 69% of sample). There was also a high poly-substance (PS) use class (n = 34, 2 % of sample), which is higher than all other classes in illicit substance use, but also had high licit SU with the exception of caffeine. There were other classes with differing patterns of poly substance use, with many being predominately high in one particular substance as indicated by the greatest SD above the mean, but also including different degrees and severity of other substance use, which were relatively high throughout. For instance, there was a predominate nicotine/licit substance use class (n = 331, 18% of sample), a predominate benzodiazepine/low overall PS class (n = 78, 4% of sample), a hallucinogen predominate/low illicit PS use class (n = 30, 2% of sample), a stimulant predominate/moderate illicit PS use class (n = 38, 2% of sample), a cocaine predominate/moderate illicit PS class (n = 18, 1% of sample), and an opioid predominate/moderate illicit PS use class (n = 41, 2% of sample). There was less class differentiation in licit substance use, such as caffeine, alcohol, nicotine, and somewhat with cannabis, for which legality varies based on geographic region of the United States. Illicit substances had greater variability among the classes and show that PS use is high for most of the classes which involved illicit drugs.

Figure 1

Plot of Mean Structure for Each Latent Class from the Final 8-Class Model of Drug Use Patterns



Note: Y-axis reflects factor scores from latent variable model in which typical and heavy quantity x frequency indices were used as indicators of each drug use latent factor. Caf = caffeine, Alc = alcohol, Can = cannabis, Cig = tobacco, Hal = hallucinogens, Ben = benzodiazepine, Opi = opioids, Coc = cocaine, and Me = stimulants.

Table 2 shows odds ratios for how the higher order personality trait domains of negative affect, antagonism, disinhibition, detachment, and psychoticism predict each of the classes. The referent used in the analyses was the little/no use group. Age and gender were adjusted in each regression. Results for age and gender are located in the appendix (see Table A1). Disinhibition was related to higher likelihood of being in the nicotine predominate class, but higher psychoticism was related to higher likelihood of being in the little/no use class. Effect sizes were below Cohen's lower bound for a small effect. Higher antagonism was related to higher likelihood of being in the cocaine predominate class, with higher detachment being related to higher likelihood of being in the little/no use class. Both were associated with small effect size with detachment being below Cohen's lower bound for a small effect. The hallucinogen predominate class was not different than the no/low use class. Higher negative affect and disinhibition were related to higher likelihood of being in the opioid predominate class with small effect size for both traits. However, results show that higher psychoticism was related to higher likelihood of being in the little/no use class. Higher negative affect was related to higher likelihood of being in the benzodiazepine predominate class with small effect size for negative affect but also showed that higher detachment was related to higher likelihood of being in the little/no use class. Higher negative affect was related to higher likelihood of being in the stimulant predominate class, with a small effect size, but higher psychoticism was related to higher likelihood of being in the little/no use class with a small effect size. High antagonism and psychoticism were related to higher likelihood of being in the high poly-substance use class with small effect sizes. High disinhibition was related to higher likelihood of being in high PS use class with a moderate effect size.

Table 2
Odds Ratios for Higher Order Domains of Negative Affect, Antagonism, Disinhibition, Detachment, and Psychoticism Predicting Classes

	Nicotine predominate/ licit PS	Benzodiazepine predominate/ low PS(all)	Hallucinogen predominate/ Low illicit PS	Stimulant predominate/ moderate illicit PS	Cocaine predominate/ moderate illicit PS	Opioid predominate/ modPS(illicit)	High PS
NA	0.97	1.99*	1.23	1.84*	1.70	1.81*	0.57
ANTAG	1.18	0.86	1.36	0.93	2.34*	1.02	1.67*
DISIN	1.34*	0.87	1.32	1.26	1.52	1.61*	3.73*
DETACH	0.86	0.69*	0.92	0.87	0.41*	0.78	0.95
PSYCHO	0.78*	0.97	0.84	0.63*	0.70	0.70*	2.33*

Note: NA = Negative Affect, ANTAG = Antagonism, DISIN = Disinhibition, DETACH = Detachment, PSYCHO = Psychoticism.
* = Indicates significance. Values in table are odds ratios. Criteria for significance was p <.05.

Next, individual facet level traits that were hypothesized to predict the SU classes were considered. Facet level traits used in individual analyses were affective lability, anger, anhedonia, anxiousness, depressiveness, irresponsibility, mistrust, non-perseverance, non-planfulness, norm violation, rigidity, and risk taking. Table 3 shows results of further analyses comparing classes to the little/no use class, along with the odds ratios for how facet level traits predict each of the substance use classes. Age and gender were adjusted in each regression. Results for age and gender are located in the appendix (see Table A2). Affective lability was related to higher likelihood of being in the benzodiazepine/low PS use class and stimulant predominate/moderate illicit PS use class with small effects. Affective lability was related to higher likelihood of being in the cocaine predominate/moderate illicit PS use class, opioid predominate/moderate illicit PS use class, and high PS class with moderate effect sizes. Anger was related to a higher likelihood of being in the stimulant predominate/moderate illicit PS use class, cocaine predominate/ moderate illicit SU class, the opioid predominate/moderate illicit SU class, each with small effect sizes, while anger was related to a higher likelihood of being in the higher PS use class with a moderate effect size. Anhedonia was related to a higher likelihood of being in the benzodiazepine/low PS use class, stimulant predominate/moderate illicit PS use class, cocaine predominate/ moderate illicit SU class, and opioid predominate/moderate illicit PS use class with small effect sizes. Anhedonia was related to a higher likelihood of being in the high PS use class which had a moderate effect size. Anxiousness shows a greater likelihood of being in the benzodiazepine/low PS use class, stimulant predominate/moderate illicit PS use class, opioid predominate/moderate illicit PS use class with small effect sizes, while anxiousness was related to a higher likelihood of being in the high PS class with a moderate effect size.

Table 3

Odds Ratios for 12 facet-level traits of Affective Lability, Anger, Anhedonia, Anxiousness, Depressiveness, Irresponsibility, Mistrust, Non-perseverence, Non-planfulness, Norm Violation, Rigidity, and Risk Taking Predicting Classes

	Nicotine predominate/ licit PS	Benzodiazepine predominate/ low PS(all)	Hallucinogen predominate/ Low illicit PS	Stimulant predominate/ moderate illicit PS	Cocaine predominate/ moderate illicit PS	Opioid predominate/ modPS(illicit)	High PS
AFFLAB	0.98	1.47 *	1.45	1.75*	2.55*	2.55*	2.7*
ANG	0.98	1.31	1.37	1.56*	1.94*	1.54*	3.03*
ANHED	0.98	1.51 *	1.15	1.7*	1.61 *	1.65*	2.51*
ANX	0.98	1.78*	1.36	1.53*	1.36	1.61*	1.97*
DEP	0.98	1.48*	1.21	1.68*	1.48*	1.67*	1.86*
IRRES	1.08	1.19	1.24	1.29	1.99*	1.58*	4.44*
MISTR	1.11	1.25	1.52*	1.35	1.63*	1.57*	2.5*
NONPER	0.97	1.17	1.47	1.51*	1.91*	1.39*	2.57*
NOPLAN	1.3	1.31	1.65*	1.37	2.38*	1.77*	5.28*
NORMV	1.7*	1.38*	3.39 *	1.58*	4.17*	3.67*	5.07*
RIGID	1.03	1.1	1.62*	1.15	2.45*	1.15	4.31*
RISK	1.18	1.07	1.84 *	1.26	2.38*	2.15*	5.16*

Table 3

Note: AFFLAB = Affective Lability, ANG = Anger, ANHED = Anhedonia, ANX = Anxiousness, DEP = Depressiveness, IRRES = Irresponsibility, MISTR = Mistrust, NONPER = Non-Perseverance, NOPLAN = Non-Planfulness, NORMV = Norm Violation, RIGID = Rigidity, RISK = Risk Taking. * = Indicates significance of p< .05.

Depressiveness was related to a higher likelihood of being in the benzodiazepine/low PS use class, stimulant predominate/moderate illicit PS use class, cocaine predominate/ moderate illicit SU class, opioid predominate/moderate illicit PS use class, and high PS use class. Effects were small. Irresponsibility was found to show a greater chance of being in the cocaine predominate/ moderate illicit SU class with a moderate effect. Irresponsibility was also related to a higher likelihood of being in the opioid predominate/moderate illicit PS use class with small effect size, and in the high PS use classes, with a large effect size. Mistrust was related to a greater likelihood of being in the hallucinogen predominate/low illicit PS use class, cocaine predominate/ moderate illicit SU class, opioid predominate/moderate illicit PS use class where effects were small, and high PS class with a moderate effect. Non-perseverance was shown to be related to a higher likelihood of being in the stimulant predominate/moderate illicit PS use class, cocaine predominate/ moderate illicit SU class with small effects, and in the high PS use class, with a moderate effect size. Non-planfulness was related to a higher likelihood of being in the nicotine predominate class with effects below Cohen's lower bound for a small effect. Non-planfulness was related to a higher likelihood of being in the hallucinogen predominate/low illicit PS use class and opioid predominate/moderate illicit PS use class with small effects, while the cocaine predominate/ moderate illicit SU class with moderate effects, and the high PS use class with a large effect size. Norm violation was related to a higher likelihood of being in all of the classes, with effect sizes ranging from small to large: the benzodiazepine/low PS use class was below the lower bound for Cohen's small effect size, while the nicotine predominate class and the stimulant predominate/moderate illicit PS use class had small effects, the hallucinogen predominate/low illicit PS use class and the opioid predominate/moderate illicit PS use class had moderate effect sizes and the cocaine predominate/ moderate illicit SU class and high PS use class had large effect sizes. Rigidity was related to higher likelihood of being in the hallucinogen predominate/low illicit PS use class with small effects; the cocaine predominate/ moderate illicit SU class with a moderate effect; and high PS use class with large effect sizes. Finally, risk taking was related to a greater likelihood of being in the nicotine predominate class with effects below Cohen's bound for a small effect size; the hallucinogen predominate/low illicit PS use class with a small effect size; the cocaine predominate/ moderate illicit SU class and opioid predominate/moderate illicit PS use classes with moderate effect size; and the high PS use class with a large effect size.

Chapter 3

Discussion

Many studies have considered the role personality plays in substance use and some research has even considered multiple drugs at once, but little research has considered patterns of substance while assessing many of the more and less commonly used substances. While a few studies have analyzed patterns of substance use using latent class analysis, these studies did not assess how traits predict patterns of substance use. To address these gaps in the literature, latent class analyses was used to assess patterns of SU (caffeine, nicotine, alcohol, cannabis, hallucinogens, benzodiazepine, cocaine, methamphetamine, and opioids) and explore how pathological personality traits predict patterns of use. Results suggested that PS use was common, with variations in primary substance of choice among classes and greater variability found in the rarer used, illicit substances. The findings were aligned with hypotheses that there would be groups of licit and illicit substance using classes, as well as more PS use in classes with illicit or “illegal” substance use. Results indicated that each higher order domain of personality had an effect on the SU classes with some being protective and some increasing risk. At the facet level, as severity in the amount of PS use and use of illicit drugs increased, personality had more effects and effects were larger. In fact, all facet level traits of interest were related to a greater likelihood of being a part of the high PS use class. Each of these points will be discussed in turn.

Patterns of SU in the Latent Class Analysis

Like previous work by Agrawal et, al (2007) and Quek et. al (2013), our study observed a little to no use class, a high PS use class, and a variety of classes in between. This study considered quantity and frequency of SU opposed to previous diagnoses of a SUD or dichotomous (yes/no) responses to substance use. Other differences in this study were that there were more classes extracted than in previous research and there was a predominate substance in each of the classes, with the exception of the high PS use class and the little/no use class. There was not as much class differentiation in the use of licit substances across classes, with the cigarette predominate class being the one class with only licit PS use. This is somewhat in accord with results of Quek et al. (2013) that found a class with primarily licit SU and supports one hypothesis of this study that there would be a class inclusive of licit or more socially accepted substances. However, licit SU did cut across all classes in this study, which was expected among substance users. Some interesting differences found were when considering the less commonly used substances. For instance, there was greater variability in use of illicit substances when considering the classes with predominate hallucinogen, benzodiazepine, opioid, cocaine, and simulant use.

It is important to consider how those groups varied in PS use. As expected, the opioid, benzodiazepines, hallucinogen, cocaine, and stimulant predominate use classes were high on the use of other substances supporting the notion that frequent use of less frequently used illicit substances involves very high PS use across licit and illicit substances (Agrawal, et al., 2007). There are many plausible explanations for these patterns. Perhaps the high rates of co-use can be explained by considering synergistic effects such as "enhancing" the effects of other substances. In other cases, they may be used to offset the negative aspects of certain drugs (Connor, et al., 2014). As an example, opioid users report using cocaine or other stimulants to experience a greater effect or in other cases to combat effects that were undesirable (Trujillo, Smith, & Guaderrama, 2011). In the case of opioids with stimulants, the stimulant or cocaine counteracted the sedative effects of the opioid, which in some instances was used to decrease anxiety or irritability from stimulant use (Trujillo, Smith, & Guaderrama, 2011). Another consideration is the positive and negative reinforcement of these substances, which is also what gives them high abuse potential (Everitt & Robbins, 2005; de Wit & Phan, 2010; Koob, 2013). Although substances have different specific processes that work in the brain, there are general neural mechanisms such as activation of the mesocorticolimbic dopamine system, which has been linked to addiction (Koob & LeMoal, 2008; Volkow, Fowler, & Wang, 2003; Volkow, Michaelides, & Baler, 2019). Many substances, with the exception of some hallucinogens, have high potential for abuse or even dependence due to the changes in the brain that occur with heavier levels of use, which can possibly explain the high PS use (Koob & LeMoal, 2008; Volkow, Michaelides,& Baler, 2019).

Higher Order Traits and Patterns of Substance use

Disinhibition (DeWitt, 2009), negative affect (Cheetam et. al, 2010), and antagonism (Sutin, Evans, & Zonderman, 2013) were related to more severe substance use, which supports previous findings (Cloninger, 1988; Gullo, et al., 2014; McCormick, et al., 1998). Disinhibition and negative affect were predictive of many of the classes which reported PS, which was expected given a large literature. Disinhibition and impulsivity are higher among substance users compared to non-substance using individuals or healthy controls (DeWitt, 2009; Sher & Trull, 1994). Negative affect has also been shown to be related to risky SU as well as the maintenance of use, which could be explained by considering negative affective states and coping skills of the individual (Cheetham, Allen, Yücel, & Lubman, 2010; Stasiewicz & Maisto, 1993). As Hogarth (2020) points out, both animal and human studies show that goal driven drug use and expectations of substance effects are shown to be related to negative affective states. Hogarth (2020) showed that both humans and animals worked toward the goal of obtaining and using a substance or substances with the expectation that the drug will eliminate the negative affective state being experienced. Antagonism was predictive of the high PS use and cocaine using classes, which can be related to risk taking and norm violation of users of illicit substances and supports previous findings of illicit substance using individuals being low on agreeableness and conscientiousness (Sutin, Evans, & Zonderman, 2013). Interestingly, the hallucinogen predominate class was not different than the least severe substance use class. One explanation of this finding is that most hallucinogens have not shown any physiological or psychological dependence syndrome (Koob & Volkow, 2010; Volkow, Michaelides, & Baler, 2019). The high PS use class was higher on psychoticism than the little/no use class, which was expected given the high PS use. The nicotine predominate class, opioid predominate class, and stimulant predominate classes were lower in psychoticism when compared to the low/no use class, but the effects were small. It could be speculated that those in the little/no use class are potentially exhibiting schizotypy or schizotypichal traits and experience unusual beliefs and unusual experiences. The non-social aspects could be protective against substance use and could explain the small effect size of psychoticism in the little/no use class. Detachment was lower in the benzodiazepine predominate and cocaine predominate use class when compared to the little/no use class. Detachment is not only the tendency to be more distant and reserved or introverted, but also related to difficulties with experience and expression of feelings (CAT-PD SF with Validity Scales; Wright & Simms, 2014). As such, this could be due to the effects of the substance, which causes less social withdrawal. Boys, Marsden, & Strang (2001) found that for cocaine users, the use of cocaine can make users feel more confident by decreasing inhibition and enjoy company when using cocaine, which in turn could explain less detachment by facilitating more social interaction. Benzodiazepines are often used to treat anxiety and can be useful in managing anxiety symptoms or taking them away altogether (Guina & Merrill, 2018). Given the behavioral disinhibition that benzodiazepines can cause, it may actually cause individuals to be less detached and more likely to engage in extroverted behaviors. Another explanation could be that the participants who endorse using those substances are more extroverted than the little/no use class, which may or may not be a result of the particular substance's affects (Crego et al., 2015; Samuel et al., 2012). Also, important to note is the reciprocal nature of personality and SU. Research has suggested both that traits are risk factors as well as results of substance use and that there is also a reciprocal relationship between traits and substance use (Stein, Newcomb, & Bentler, 1987; Turiano, et al., 2012).

Facet Level Traits and Patterns of Substance Use

The hypothesis that the licit SU classes would only be likely to have the trait of anxiousness compared to the illicit using classes, was not supported by the data. Although it was believed that anxiousness could be a protective factor against illicit SU as it is similar to harm avoidance (Milivojevic, et al., 2012), the results did not suggest a difference. On the contrary, the high PS use class, along with opioid predominant, benzodiazepine predominate, and stimulant predominate classes were instead higher than the little/no use class on anxiousness. Although it was thought to potentially be a protective factor against SU, it may in some instances be motivation for using substances in an effort to alleviate anxiousness. This can also be explained by considering that particular substances, used frequently enough may cause dependence, which can also drive stress, anxiety or fear of experiencing withdrawal syndrome (Hogarth, 2020; Koob & Le Moal, 2008; Koob & Volkow, 2010). Another consideration is that causation is difficult to establish between substance use and personality traits.

Another interesting finding was that the only trait that the tobacco predominate/low licit SU class was more likely to have compared to little/no use class was norm violation. Perhaps the norm violation in the nicotine predominate/low licit PS use class is the only predictive trait when compared to the little/no use class because nicotine use could be considered deviant relative to no use. This may be due to the negative views society has adopted about tobacco smoking and the realization of its harmful effects (Abrams, et al., 2018). Those in the nicotine predominate/low licit PS use class do not endorse using other substances that are illicit.

Results supported the hypothesis that more severe levels of PS use and illicit SU would yield higher likelihood of pathological personality traits, as found in previous literature (Wu, et al., 2011; Conway et al., 2002; Conway et al., 2003). When considering affective lability, anhedonia, depressiveness, and norm violation, the moderate to high PS use classes were all more likely than the little/no use class or low PS use classes to be predicted by those traits. The high PS use class was more likely than the little/no use class to endorse *all* of the facet level traits consistent with previous research and hypotheses (McCormick et al., 1998). This could be due to high comorbidity of anxiety, depression, and other mental health disorders with SU and SUD (Lai, et al., 2015). Although the current study did not assess for or confirm SUD among participants or if there are other mental illnesses present, there was reported SU which could very well cause more pronounced pathological traits than non-using participants. More specifically, comorbidity of personality disorders is often higher in those with SUDs than the general population (Parmar & Kaloiya, 2018). The opioid predominate/ moderate illicit PS use class had higher endorsements of pathological traits with the exception of rigidity. Similarly, the cocaine predominate/moderate illicit PS use class was also predicted by all hypothesized facet level traits except anxiousness. Another surprising result was that in direct opposition to prior research (Conway et al., 2002; Conway et al., 2003; Ersche, et al., 2010; Ersche, et al., 2012; Ersche, et al., 2013), risk taking was not predictive of the stimulant predominate/moderate illicit PS use class. Once again, this could be explained by considering there have been varying results when it comes to PS use, as it could be due to another substance or the combination or mixture of many substances being used (Conway et al., 2002; Conway et al., 2003). Affective lability, anger, anhedonia, anxiousness, depressiveness, non-perseverance, and norm violation was related to a higher likelihood of being in the stimulant predominate/moderate illicit PS class. Interestingly, those facet level traits are part of the higher order domain of negative affect, with the exception being norm violation, which loads onto antagonism and disinhibition. This could potentially be due to effects of stimulant use as well as considering some of the withdrawal symptoms from stimulants that include anhedonia, anxiousness, and depressiveness (Weaver & Schnoll, 1999). Perhaps similar to cocaine and other SU, stimulant predominate users are using stimulants for negative reinforcement in an attempt to remove experiences due to the traits of anhedonia, anxiousness, and depressiveness (May, Aupperle, & Stewart, 2020). A possible explanation for affective lability being more likely in the stimulant predominate class could be that use of stimulants or multiple substances together can trigger emotional and mood dysregulation (Darke, et al., 2008). Non-perseverance could be either a result of or a reason an individual is using stimulants considering stimulants can increase perseverance. For instance, it has been found that stimulant use by college students are usually for purposes of concentration, alertness, and memorization (Smith & Farah, 2011). Many times, college students report using stimulants to study or memorize material due to procrastination, low self-efficacy, or motivational factors (Sattler, et al., 2014; Looby, Beyer, & Zimmerman, 2015). Although the current study has a broader range than college students, the explanation of non-perseverance still applies since stimulants can improve perseverance for anyone among the broader population using stimulants. Also, when considering the norm violation of the stimulant predominate class, that finding is aligned with results suggesting individuals who use illicit substances are more likely to go against societal norms, which is also applicable when considering other illicit substances (Galea, Nandi, & Vlahov, 2004).

Limitations

A main limitation of this study was using an online platform as a recruitment and data collecting tool. Although data collected online is often a more efficient method, it does pose risks of possible bots or software designed to complete surveys solely to collect financial gain, which can be a detriment to good data collection. However, there were preventative measures used to mitigate that risk. Second, all constructs in the present study were self-report, in which participant's responses can be biased (Choi & Pak, 2005; Van de Mortel, 2008). Although there are advantages when collecting data through self-report, there can be response bias from participants which could cause the data to be inaccurate and affect the results. There is also potential that participants may interpret questions differently than they are intended to be understood.

Another important limitation to consider is that the design of the study was cross-sectional and not longitudinal. Without data to indicate the duration of SU or what stage of use an individual is in, along with reassessing personality traits over time to ascertain if or how they may change, it becomes a challenge to differentiate whether these trait domains are the result of substance use or if they were perhaps risk factors leading to these specific patterns of use. Previous and current literature has shown support for both conclusions (Stein, Newcomb, & Bentler, 1987; Turiano, et al., 2012).

A specific limitation which would be interesting for future research was that there was no separation or distinction between specific substances within drug categories. Most substance categories asked which specific drug was used, once that category was endorsed (e.g. heroin, oxycontin, hydrocodone, etc.), but there was no further investigation regarding how specific substances may differ within drug categories. Although specific substances were included in their overall drug category, it is important to consider that some may have different effects than others. A major category included in this study that did not ask any further substance specific questions was hallucinogens, which are a diverse group of drugs that may have different effects on the brain. Also, some substances can be considered a part of other drug categories, which means they potentially belong to other substance categories as well. For instance, this can be seen when considering hallucinogens like MDMA, which has the properties of a stimulant with a behavioral profile of a hallucinogen (Gold, Koob, & Geyer,1988). Included in this study were hallucinogens, which are a diverse group of drugs that may have different effects on the brain. It is important to note that although these substances are all considered hallucinogens, they may have different trait effects, as well. Some examples would be comparing PCP, which is also a dissociative substance (Morris & Wallach, 2014); psilocybin, considered a classic psychedelic; and MDMA, which is more of an entactogen or a "touching within" that produces feelings of euphoria (Roseman, et al., 2014). The same point could be considered with other categories as well, such as stimulants, opioids, cannabis, and cocaine. For this study, we considered the categories that the substances are grouped under, but for future research a separation of those substances may be necessary, so that those different associations with personality could potentially be parsed out. For instance, users of crack may be very different from users of cocaine, just as differences of intravenous heroin users may be observed compared to users of hydrocodone. This would also help to see similarities as well. Future directions in research could potentially see differences when considering specific substances within drug categories.

Simple improvement or replication of the current study would be valuable in itself, especially if it was done longitudinally.

Conclusion

Results suggested that PS use was common, with variations in primary substance of use among classes. As expected, greater variability was observed in substances that are the least likely used and less variability in licit SU, since it is more common for those substances to be used among the general population. Also, severity of SU and greater PS use is predicted by more pathological traits. Although PS use poses the challenge of deciphering if and which traits are predicting specific SU or inferring if it is the result of the combinations of those substances, there is still valuable information observed in the data. Overall, this study has found that pathological personality traits are able to predict certain patterns of SU. It also shows that illicit PS use severity and range of use can be used in considering level of pathology. Some main findings were that more severe and varied PS use can be predicted by negative affect, disinhibition, and antagonism.

This study adds to the field by advancing knowledge of how SU patterns are likely to cluster together within people as well as how facet level traits predict those classes of patterns. The current work also gives insight to novel information for better understanding the relationship between SU and personality traits. This will hopefully inform prevention models and treatments of SU and SUDs by helping to understand certain traits that may be strengths or weaknesses of individuals. Future research on this topic could expand further by focusing on specific drug of choice by asking what the drug of choice is and then investigating how that is related to patterns of use, as well as how different personality traits may predict those preferred drugs. Another interesting direction would be to consider if and how traits predicted specific substance use within drug categories, as well as exploring how different substances within drug categories may have different effects.

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Appendix

Older age and male gender were related to higher likelihood of being in the nicotine predominate class. Older age was related to higher likelihood of being in the little/no use class as well as the benzodiazepine predominate class. Male gender was related to higher likelihood of being in the stimulant predominate, opioid predominate, and high PS use classes.

Table A1

Odds Ratios for Age and Gender for Classes on Domain Level Traits

	Nicotine predominate/ licit PS	Benzodiazepine predominate/ low PS(all)	Hallucinogen predominate/ Low illicit PS	Stimulant predominate/ moderate illicit PS	Cocaine predominate/ moderate illicit PS	Opioid predominate/ modPS(illicit)	High PS
Age	*1.02	*1.03	1.04	1.01	1.02	1.02	1.01
Gender	*1.42	1.43	1.01	*0.46	1.92	*0.42	*2.52

Older age was related to higher likelihood of being in the nicotine predominate class and benzodiazepine predominate class for all facet level traits. Male gender was related to higher likelihood of being in the benzodiazepine predominate class for all facet level traits. Male gender was related to a higher likelihood of being in the nicotine predominate class for the traits of non-planfulness, norm violation, and risk taking. Older age was related to a higher likelihood of being in the hallucinogen predominate class for the facet level traits of anger, anhedonia, depressiveness, irresponsibility, mistrust, and rigidity. Male gender was related to a higher likelihood of being in the stimulant predominate class for the trait of anxiousness. Male gender was also related to a higher likelihood of being in the opioid predominate class for the facet level traits of affective lability, anger, anhedonia, anxiousness, depressiveness, mistrust, non-perseverance, and rigidity.

Table A2

Odds Ratios for Age and Gender for Classes on Facet Level Traits

	Nicotine predominate/ licit PS	Benzodiazepine predominate/ low PS(all)	Hallucinogen predominate/ Low illicit PS	Stimulant predominate/ moderate illicit PS	Cocaine predominate/ moderate illicit PS	Opioid predominate/ moderate PS(illicit)	High PS
AFFLAB							
Age	1.02*	1.03*	0.96	1	1.01	1.02	0.99
Gender	1.24	1.98*	0.75	0.75	1.21	0.38*	0.8
ANG							
Age	1.02*	1.02*	0.96*	0.99	1	1.02	0.99
Gender	1.24	2.04*	0.77	0.5	1.34	0.39*	0.8
ANHED							
Age	1.02*	1.02*	0.96*	0.99	1	1.02	0.99
Gender	1.23	2.22*	0.81	0.57	1.56	0.44*	1.06
ANX							
Age	1.02*	1.03*	0.96	1	1	1.02	0.99
Gender	1.24	1.69*	0.7	0.45*	1.3	0.35*	0.71
DEP							
Age	1.02*	1.02*	0.96*	1	1	1.02	0.99
Gender	1.23	2.02*	0.78	0.5	1.4	0.39*	0.86
IRRES							
Age	1.02*	1.02*	0.96*	0.99	1	1.02	1
Gender	1.25	2.19*	0.84	0.56	1.71	0.46	1.25
MISTR							
Age	1.02*	1.02*	0.96*	0.99	1	1.02	0.99
Gender	1.23	2.11*	0.79	0.53	1.45	0.41*	0.89
NONPER							
Age	1.02*	1.02*	0.96	0.99	1	1.02	0.99
Gender	1.23	2.13*	0.81	0.54	1.51	0.42*	0.97

NOPLAN							
Age	1.02*	1.02*	0.96	0.99	1.01	1.02	1
Gender	1.3*	2.23*	0.9	0.57	1.8	0.47	1.36
NORMV							
Age	1.02*	1.02*	0.96	0.99	1.01	1.03	1
Gender	1.46*	2.34*	1.21	0.62	2.42	0.66	1.65
RIGID							
Age	1.02*	1.02*	0.95*	0.99	0.96	1.01	0.98
Gender	1.24	2.16*	0.9	0.55	1.84	0.45*	1.38
RISK							
Age	1.02*	1.02*	0.96	0.99	1.01	1.03	1.01
Gender	1.31*	2.17*	1	0.58	2.04	0.56	1.66

Note: AFFLAB = Affective Lability, ANG = Anger, ANHED = Anhedonia, ANX = Anxiousness, DEP = Depressiveness, IRRES = Irresponsibility, MISTR = Mistrust, NONPER = Non-Perseverance, NOPLAN = Non-Planfulness, NORMV = Norm Violation, RIGID = Rigidity, RISK = Risk Taking. * = Indicates significance.

VITA

The author was born in Metairie, Louisiana. She obtained her Bachelor's degree in psychology from the University of New Orleans in 2016. She joined the University of New Orleans psychology graduate program to pursue a PhD in applied developmental psychology, and became a member of Dr. Matthew Scalco's research lab in 2017, respectively.