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Patterns of Substance Use and Associations with Mental, Physical and Social Functioning: A Latent Class Analysis of a National Sample of U.S. Adults Ages 30-80

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Abstract

Objective.—Trends show increased substance use among adults, yet little research on general population samples has examined differential patterns of licit and illicit substance use that can inform prevention and treatment efforts. This study identifies distinct patterns (classes) of substance use among 30-80 year olds, identifies demographic subgroups with the highest probability of class memberships, and compares classes on key indicators of functioning.

Method.—Participants (n=1,877) were from the RAND American Life Panel. Online survey measures included current alcohol, tobacco, cannabis, and nonmedical prescription drug use, as well as mental, physical and social functioning.

Results.—Latent class analysis identified four classes: *'Lighter Drinking'* (46.6%), *'Abstaining'* (33.7%), *'Heavy Drinking with Cigarette/Cannabis Use'* (17.1%), and *'Cigarette Smoking with Prescription Drug/Cannabis Use* (2.6%). Of these classes, *'Cigarette Smoking with Prescription Drug/Cannabis Use'* reported the worst mental and physical functioning, and greater loneliness than the *'Lighter Drinking'* class. *'Heavy Drinking with Cigarette/Cannabis Use'* reported worse mental and physical functioning than the *'Lighter Drinking'* class and less social support than the *'Lighter Drinking'* and *'Abstaining'* classes. The *'Abstaining'* class reported consistently worse functioning than the *'Lighter Drinking'* class. Both polysubstance use classes were associated with younger age, less education, and lower income, and heavy drinking polysubstance use was associated with being male and unmarried.

Conclusions.—Although lighter drinking was the most common pattern, 20% of adults were classified into two polysubstance use classes associated with poorer functioning. Targeted efforts may be needed to reach certain subgroups of adults who are particularly susceptible to polysubstance use.

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Ethical Approval. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent. Informed consent was obtained from all individual participants included in the study.

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Keywords

alcohol; tobacco; cannabis; prescription drugs; latent class analysis

INTRODUCTION

Although rates of alcohol and illicit drug use tend to decline after young adulthood (SAMHSA, 2019; Lehmann & Fingerhood, 2018), they are by no means negligible or inconsequential during mid- and later-life (Kuerbis et al., 2014). For example, rates of past year alcohol and illicit drug use are 77.9% and 27.5% (respectively) among 30-34 year olds, 75.0% and 19.3% among 40-44 year olds, and 63.2% and 10.5% among those age 50 or older (SAMHSA, 2019). Aging of the Gen X and Baby Boomer generations is happening in the context of expanding access to an array of traditional and emerging alcohol, cannabis, tobacco, and other substance use products (e.g., Kasza et al., 2017; Steigerwald et al., 2018). Demographic trends show an increase in alcohol use and disorder among mid- and later-life adults (Grant et al., 2017; Han et al., 2017a); this is also the case for cannabis (Han et al., 2017b) and the nonmedical use of prescription drugs (Schepis & McCabe, 2016; Wu & Blazer, 2011). Consistent with these trends, an analysis of substance abuse treatment admissions among adults aged 55 and older, for example, showed an increase between 2000-2012 in admissions for cannabis use and misuse of prescription drugs as the primary substance (Chhatre et al., 2017).

Much of what is known about substance use among adults comes from large-scale epidemiologic studies and surveys that focus on assessing prevalence and incidence of single substances (e.g., SAMHSA, 2019). While important, identifying distinct patterns of use across multiple substances provides unique information that can help inform the work of researchers, practitioners, and policymakers. For example, identifying which substances tend to be used together can be key to informing public health campaigns, treatment approaches, and other efforts to reduce polysubstance use. It is also important to understand whether adults with certain patterns of use may be at particularly high risk of experiencing poor physical, mental, or social functioning. Finally, understanding whether demographic subgroups tend to engage in certain patterns of substance use can further our understanding of substance use-related health disparities and identify subgroups that may especially vulnerable and in need of targeted outreach and treatment efforts. Latent class analysis (LCA; Rindskopf, 2009) is a statistical approach that allows for the identification of substance use patterns that are not specified by the researcher a priori; as such, it can identify unobserved clusters in the data and potentially yield insights about phenotypes (“classes”) of substance users (Collins & Lanza, 2009; Masyn, 2013). In contrast to traditional variable-centered approaches that examine variables individually, person-centered approaches such as LCA assume sample heterogeneity and identify subgroups of individuals with shared characteristics (Berlin et al., 2014).

Numerous studies have used LCA to identify patterns of substance use among adolescents and young adults (e.g., Cadigan et al., 2019; Evans-Polce et al., 2016; Haardörfer et al., 2016). However, studies using LCA to identify substance use patterns in samples of adults beyond the college years have tended to focus on patterns of use within a single substance (e.g., Linden-Carmichael et al., 2019; Sacco et al., 2009), patterns of risk behaviors that include, but are not limited to, substance use (e.g., Choi et al., 2015; Cook et al., 2020), or patterns of use in special populations such as veterans (e.g., Green et al., 2010), men who have sex with men (Card et al., 2018), or individuals who use a particular substance (e.g., Harrell et al., 2014). General population studies of adults that have used LCA to identify classes based on multiple types of substances have been largely limited in their focus on illicit drug use only or substance abuse/dependence. For example, one study used LCA to identify patterns of past year illicit drug use among adults from the U.K., Australia, and the U.S. who participated in the Global Drug Survey (Morley et al., 2015). Based on reports of cannabis, ecstasy, cocaine, stimulants, nitrous, ketamine, benzodiazepines and opioid painkiller use, six classes of use were identified: no polysubstance use; cannabis and ecstasy; all illicit drugs; ecstasy and cocaine; cannabis and medication; and all drugs. Other studies have used LCA to derive lifetime illicit drug use disorder classes using data from the National Epidemiological Survey on Alcohol and Related Conditions (NESARC). For example, one such study identified four classes of lifetime substance use disorder: a very low risk class; a class with high opioid, sedative and heroin comorbidity; a class based on cocaine and stimulant comorbidity; and a class with high likelihood of multiple lifetime drug use disorders (Hochheimer et al., 2020). An earlier study using NESARC data identified five latent classes of lifetime illicit drug abuse/dependence: no abuse/dependence; cannabis only; stimulants and hallucinogens; prescription drug; and polysubstance (Agrawal et al., 2007). Importantly, none of these studies included two of the most commonly used substances by adults: alcohol and tobacco/nicotine.

The present study addresses an important gap in this literature by using LCA to identify patterns of current substance use in a national sample of 30-80 year olds in the U.S., focusing on commonly used licit and illicit substances in this age group: alcohol, tobacco/ nicotine, cannabis, and prescription drugs for nonmedical purposes. Extending prior research in this area, we use ordinal indicators that differentiate the frequency of use (e.g., no use, non-daily use, daily/near daily use) rather than binary indicators (no use vs. use), as well as differentiate between vaped and non-vaped use of tobacco/nicotine and cannabis products. The first goal of this study was to define classes of substance use in terms of individuals' trichotomous (never, non-daily/non-heavy, daily/heavy) probabilities of having used each of these substances in the past 30 days. After identifying distinct classes of substance use, the second goal of this study was to compare these classes on indicators of physical, mental, and social functioning to determine whether certain patterns of use might pose greater risks for adults. Finally, we sought to identify subgroups of adults who may be particularly vulnerable to certain patterns of substance use by using latent class regression analysis to examine associations of sociodemographic characteristics (e.g., age, gender, race/ethnicity) with class membership.

METHODS

Participants and Procedures

An initial random sample of 2,615 adults between the ages of 30-80 from the RAND American Life Panel (ALP; Pollard & Baird, 2017) were invited to complete personal and network surveys (only data from the former was used in the present study). The ALP is a national Internet panel of over 5,000 U.S. adults who were ages 21 and older at the time of data collection. ALP members are initially recruited into the panel via probability-based sampling methods, either sampled by random digit dial (landline and cell phone) or address-based sampling; individuals cannot otherwise volunteer to participate. A further advantage over most other Internet panels is that the respondents to the ALP need not have Internet access when they are initially recruited (RAND provides laptops and internet subscriptions if needed). The surveys were closed after six weeks in the field (April 29 – June 9, 2019) with 1,890 personal survey completions. For the present analyses, we excluded 9 individuals who were missing data for all of the substance use items and 4 individuals who were missing data on any of the background characteristics, resulting in an analytic sample of 1,877. Overall, the analytic sample is 48% female and the majority are white (69%); 15% are Hispanic non-white; 11% are black and 5% are other races. Most of these participants are married (61%) and have a college degree (51%). The mean age is 56 years (SD = 13.82), with 45% of the analytic sample being age 60 or older. Those who completed the survey were compensated for their time. All materials and procedures were approved by the institution's internal review board.

Measures

Past month substance use (LCA indicators).—Seven items were used as indicators of past month substance use. Participants rated the number of days that they had: (1) drank at least one full drink of alcohol; (2) engaged in heavy drinking (5 or more drinks in a row for men, 4 or more drinks in a row for women); (3) smoked cigarettes; (4) used electronic cigarettes (or e-cigarette, e.g., Blu e-cig) or personal vaporizer ("vape pen" or "mod") filled with nicotine e-liquid or other type of tobacco/nicotine product; (5) used cannabis that is smoked (e.g., joint, bong, or dab) or consumed as an edible; and (6) used electronic cigarettes (or e-cigarettes) or personal vaporizer ("vape pen" or "mod") filled with hash oil, THC wax, dried buds, or other type of cannabis product; and (7) used prescription medications without a prescription on their own or simply for the experience or feeling the drugs caused. Respondents rated their frequency of use of each substance indicator on a 7-point scale (1 = *0 days*; 2 = *1 day*; 3 = *2 days*; 4 = *3-5 days*; 5 = *6-9 days*; 6 = *10-19 days*; 7 = *20-30 days*). For most substances, response options were trichotomized to indicate *no use* (0 days), *non-daily use* (1-19 days), and *daily/near daily use* (20-30 days). The exception involved heavy drinking, where respondents were categorized as *non-drinkers* (0 days of drinking and 0 days of heavy drinking), *non-heavy drinkers* (> 0 days of drinking, but 0 days of heavy drinking), and *heavy drinkers* (> 0 days of drinking and > 0 days of heavy drinking). This re-categorization put the response options for all 7 substance use indictors on a comparable scale to allow for meaningful comparison of three types of users (i.e. non-users, non-daily/non-heavy users and daily/heavy users).

Physical functioning.—Physical functioning in the past four weeks is assessed with the 15-item Patient Health Questionnaire (PHQ-15; Kroenke et al., 2002), which asks how much participants were bothered by things like pain, dizziness, shortness of breath, constipation, indigestion, low energy and trouble sleeping (0 = *not bothered at all* to 2 = *bothered a lot*; α = 0.82). Scores can range from 0 to 30, with a cut-off of 10 or higher indicating a moderate to severe level of somatization.

Mental functioning.—There are two measures of mental functioning: depression symptoms and anxiety symptoms. Depression is assessed with the Patient Health Questionnaire - 8 item (PHQ-8; Kroenke et al., 2009) that asks about symptoms such as feeling down, depressed, or hopeless and having little interest or pleasure in doing things (α = 0.92). Scores can range from 0-24, with 5, 10, 15, and 20 representing cut-points for mild, moderate, moderately severe, and severe depression, respectively. Anxiety is assessed with the Generalized Anxiety Disorder 7-item (GAD-7; Spitzer et al., 2006) that asks about symptoms such as feeling nervous, anxious, or on edge and not being able to stop or control worrying (α = 0.94). Scores can range from 0-21, with scores of 5, 10, and 15 representing cut-points for mild, moderate, and severe anxiety, respectively. Both measures assessed symptoms in the past two weeks on a scale from 0 = *not at all* to 3 = *nearly every day*.

Social functioning.—Three variables are used to assess social functioning: friend support, family support, and loneliness. Levels of satisfaction with support received from family and friends are each measured using three items (Jones, 1991): How satisfied are you… (a) with the assistance you get from your [friends, family] in daily activities such as helping you with chores, giving you information, etc; (b) with the emotional support you receive from your [friends, family] such as feeling cared about, discussing personal problems; and (c) with the socializing you do with your [friends, family]? Items are rated on a 5-point scale (1 = *very satisfied* to 5 = *very dissatisfied*; α = .88 for family, α = .86 for friends). Loneliness was assessed with the widely used 3-item UCLA Loneliness Scale (Hughes et al., 2004; α = .84), which asks how often the respondent feels that they lack companionship, feel left out, and feel isolated from others (1 = *hardly ever* to 3 = *often*).

Background characteristics.—These included whether they identified as male or female, race/ethnicity [non-Hispanic white (reference) vs. Hispanic, non-Hispanic black, and non-Hispanic other)], age (30-59 vs. 60 and older), education (college graduate vs. not), and household income.

Analytical approach

We conducted the LCA using Mplus V8 (Muthén & Muthén, 1998–2017) to model the probability of endorsing the highest category for each item (i.e., daily/heavy user). We used maximum likelihood estimation with robust standard errors to accommodate non-normal data. Mplus provides solutions that extract different numbers of latent classes. Given that our indicators were ordered categorical in nature and that we had missing data, we used the MLR (i.e. maximum likelihood parameter estimates with robust standard errors) estimator in Mplus. This estimation method uses the full data set and it generates AIC (Akaike's Information Criterion; Akaike, 1973; 1987), BIC (Bayesian Information Criterion; Schwarz,

1978) and SABIC (sample-size adjusted BIC; Sclove, 1987) as a means for model selection. Competing models were compared against each other based on model fit using AIC and BIC. We evaluated solutions with different numbers of classes based on model fit and interpretability. Model fit was compared across solutions with 1 to 5 classes to identify the optimum and most parsimonious solution. We also used the Vuong-Lo-Mendell-Rubin likelihood ratio test and the parametric bootstrap likelihood ratio test to decide the best number of classes. Entropy is a measurement of classification quality that we looked into to determine if the latent classes are clearly defined. Entropy with values approaching 1 indicate clear delineation of classes (Celeux & Soromenho, 1996). Observable demographics such as age, gender or race may influence substance use behaviors; as such, these demographic variables are included in the LCA as covariates to analyze demographic characteristics associated with potential classes. Specifically, we created dummy variables to study effects of gender (being male vs. not), race (being Hispanic vs. white; being black vs. white; being other race vs. white), marital status (being married vs. not), education level (having a college degree vs. not), age (being age 60-80 vs. 30-59 years old), and household income (using a natural log to make income more normally distributed). These covariate effects of the demographics are estimated via a multinomial logistic model as part of the LCA model. Instead of tabulating the effects of demographics in terms of odds ratios comparing two classes which could be lengthy, we present the differences in demographics across the extracted classes descriptively together with their statistical significance.

LCA estimates the probability of each participant being in each class. The highest probability of being in a certain class is then used to assign membership of that person to the class. Effects of the demographic characteristics were estimated as part of the LCA model. Given these assigned memberships from LCA, we compared the classes in terms of their substance use, as well as difference in various indicators of physical, mental, and social functioning as a follow-up step. To compare participants' physical, mental, and social functioning across the classes, we conducted pairwise comparisons of means of each functioning measure. Specifically, we made all pairwise comparisons of the functioning items using the Mixed procedure in SAS (SAS Institute Inc., 2015) that tests the differences of least squares means while adjusting for unequal variances between the groups.

RESULTS

Latent Class Analysis Results – Measurement Model

Mplus provided solutions extracting up to 5 latent classes. When comparing solutions across increasing numbers of classes, we observed all three criteria (AIC, BIC, and SABIC) decreasing, indicating improved model fit. These criteria generally favor models that produce a high log-likelihood value using relatively few parameters and are scaled such that a lower value represents a better fit (Tien, Coxe, & Cham, 2013). We chose SABIC over BIC for model selection as it was consistently decreasing. It is worth noting that limited information goodness-of-fit statistics such as CFI (Comparative Fit index; Bentler, 1990) and TLI (Tucker-Lewis index; Bentler & Bonett, 1980; Tucker & Lewis, 1973) are not available in Mplus as they are based on limited information (i.e., variances and covariances) instead of full-information (i.e., the full data set used by the MLR estimator we chose).

Table 1 compares AIC and SABIC across 2, 3, 4 and 5 class solutions. While AIC and SABIC decreased as more classes were extracted, they did not improve as drastically for solutions greater than 4 classes. The Vuong-Lo-Mendell-Rubin likelihood ratio test compares the model with K classes (here we chose 4 classes) to a model with (K-1) classes (i.e. 3 classes). This test has a *p*-value of .04 and the Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test has a *p*-value of .04. The result of the parametric bootstrap likelihood ratio test also supports the 4-class solution over the 3-class solution (p=0.00). In addition, entropy as a measurement of classification quality is 0.84, indicating clearly delineated classes. Comparing descriptive plots of extracted classes based on 2, 3, 4, and 5 class solutions, we decided that the solution with four latent classes was the most interpretable option. It not only showed better fit and better performance according to a few other test statistics than the solutions with fewer extracted classes, but also was more parsimonious than the option with 5 classes.

LCA results in Figure 1 indicate subtypes of adults based on endorsing the highest category (i.e., who is more likely to be daily/heavy users of the various substances). The four extracted latent classes are represented by a set of color-coded lines. The dots on the lines correspond to conditional probabilities (on the y-axis) of endorsing the highest category of each of the seven substance use items (i.e., daily/heavy use). For example, the probability of endorsing the highest category of item #1 (being a daily/near daily drinker) is about 21% for those in class 1, 20% for those in class 3, and zero for those in classes 2 and 4. Note that all classes had a low likelihood of reporting use of vaping products for nicotine or cannabis; thus, heretofore, references to cigarettes and cannabis refer to non-vaping forms of these substances. As shown in Figure 1 and Table 2, participants grouped in class 1 – *Heavy Drinking with Cigarettes/Cannabis* (17.1% of the sample) – are predominantly defined in terms of their high likelihood of heavy drinking, as well as moderate likelihood of daily/almost daily cigarette smoking and non-daily cannabis use. Participants in class 2 – *Cigarette Smoking with Prescription Drugs/Cannabis* - form the smallest class (2.56% of the sample). They have a moderate likelihood of non-daily and daily/near daily cigarette smoking, as well as non-daily prescription drug misuse and cannabis use, but a low likelihood of drinking. Participants in class 3 – *Lighter Drinking* – form the largest class (46.62% of the sample). These individuals have a high likelihood of non-daily alcohol use, combined with a low likelihood of heavy drinking. They also have a low likelihood of reporting tobacco, cannabis, and nonmedical prescription drug use. Finally, participants in class 4 – *Abstaining* (33.72% of the sample) – have only slightly elevated probability of daily/near daily cigarette use (< 6%).

Latent Class Analysis Results –Demographics and Functioning

The top of Table 3 shows how these four classes differ in terms of key demographics. Using class 4 (*Abstaining*) as reference group, people in class 1 (*Heavy Drinking with Cigarettes/Cannabis*) are characterized as more likely to be male, unmarried, younger and less educated (i.e. not having college degree); people in class 2 (*Cigarette Smoking with Prescription Drugs/Cannabis*) report lower income; and those in class 3 (*Lighter Drinking*) tend to be older, more educated and have higher income.

The bottom of Table 3 shows how these four classes compare in terms of physical, mental, and social functioning. The class with the least favorable profile was *Cigarette Smoking with Prescription Drugs/Cannabis*. Adults in this class tended to report worse physical functioning and mental functioning (more depression and anxiety symptoms) than each of the other three classes. In addition, the *Cigarette Smoking with Prescription Drugs/Cannabis* class reported greater loneliness than the *Lighter Drinking* class, although they did not significantly differ from the other three classes in terms of family or friend support. The *Heavy Drinking with Cigarettes/Cannabis* class, although faring better than the *Cigarette Smoking with Prescription Drugs/Cannabis* class, tended to have less social support than the *Lighter Drinking* and *Abstaining* classes. In addition, they tended to report worse mental and physical functioning than the *Lighter Drinking* class, but did not significantly differ from the *Abstaining* class. Finally, the *Abstaining* class reported worse mental functioning, physical functioning, and certain aspects of social functioning (friend support, loneliness) compared to the *Lighter Drinking* class.

DISCUSSION

Utilizing a national sample of 30-80 year olds, results from this study identified four distinct patterns of substance use in this age group. About one-third of adults were in a class that largely abstained from substance use, and nearly half were classified as lighter drinkers. The remaining 20% of adults were in one of two polysubstance use classes: one was primarily characterized by heavy drinking, but also cigarette and cannabis use, whereas the other was primarily characterized by cigarette smoking, but also nonmedical prescription drug and cannabis use. Relatively little is known about patterns of the most commonly used licit and illicit substances in general population samples of adults, including differentiating between types of polysubstance use. Our results suggest that polysubstance use among adults warrants further attention, especially given recent trends indicating an increase in the proportion of substance abuse treatment admissions involving polysubstance use (Chhatre et al., 2017).

The polysubstance use class that was predominantly defined by cigarette smoking, but also nonmedical prescription drug and cannabis use, comprised a small percentage of our sample. However, this class had a distinctly worse profile than any other substance use class in terms of physical functioning. This is perhaps not surprising given the well-established health risks associated with cigarette smoking (U.S. Department of Health and Human Services, 2014), as well as the significant and unique adverse effect that nonmedical prescription drug and cannabis use may have on the health of adults in their own right (Kuerbis et al., 2014). Further, the co-use of these substances may lead to heavier and sustained use, at least in the case of tobacco and cannabis (Agrawal et al., 2012), and thus a greater impact on physical health. Our findings also suggest that this class of polysubstance users may be particularly susceptible to comorbid depression and anxiety – even more so than the other polysubstance use class that is predominantly characterized by heavy drinking. While further research is needed to understand these group differences, this finding is particularly concerning given that increases in nonmedical prescription drug use among adults has coincided with increases in its use with suicidal intent (West et al., 2015). In contrast to differences between the two polysubstance use classes on physical and mental functioning, both classes were quite similar in their social functioning, with both reporting lower social support and greater loneliness compared to the lighter drinking and abstaining classes (although this was not statistically significant for the class predominantly defined by cigarette smoking due to the small sample size). These results for social functioning, which may indicate social isolation and low levels of support, encourage further research which systematically explores the relationship of these substance use classes to social network structure and composition. In treatment efforts, the poorer social functioning among polysubstance users should be considered (Kalapatapu & Sullivan, 2010), as these adults may be socially isolated and lack the support that they need to get treatment or reduce their use (Dobkin et al., 2002; Pettersen et al., 2019). Clearly, future efforts to educate clinicians and the general public about substance use among adults should include a focus on the potential for polysubstance use. Further, our results suggest that efforts to reduce polysubstance use among adults, particularly involving heavy drinking, may benefit from a targeted focus on subgroups who are at greatest risk: those who are male, younger, unmarried and have lower socioeconomic status.

Another key finding from this study is that the *Abstaining* and *Heavy Drinking* classes both reported worse physical and mental functioning than the *Lighter Drinking* class, but did not significantly differ from each other in these two domains, even when controlling for key demographic characteristics such as gender, marital status, and education. This pattern is consistent with studies from the alcohol literature suggesting that occasional/moderate drinking confers certain health benefits, both physically (Xi et al., 2017; Keyes et al., 2019) and mentally (Baum-Baiker, 1985; Peele & Brodsky, 2000). However, conclusions about a causal link between occasional/moderate drinking and improved health outcomes are not without controversy due to methodological limitations of the literature (e.g., Stockwell et al., 2016). For example, the present study cannot rule out that adults who were initially in poorer physical or mental health chose, depending on their situation, to abstain from substances or, at the other extreme, engage in heavy drinking. Another possibility is that these health-related class differences emerged because the *Abstaining* class was largely comprised of former heavy drinkers who had recently quit (see Liang & Chikritzhs, 2013), although this does not appear to be the case in that 96% of adults in the *Abstaining* class reported drinking just once a month or less in the past year. Further research is clearly needed to better understand differences in functioning among adults who abstain from substance use, relative to lighter drinkers and polysubstance users, given that such differences will likely have important clinical implications.

Strengths of this study include the national sample of U.S. adults, the assessment of a broad range of substances and their combined use, and the ability to compare substance use classes on several key indicators of adult functioning. Nonetheless, several study limitations should be considered when interpreting these findings. First, information on lifetime or past year use was not available for most substances, but would have allowed us to integrate information on substance use history (never, prior, or current use) into the LCA to obtain a richer picture of substance use patterns. Second, there are important differences between types of nonmedical prescription drug use, but the relatively small number of participants who reported engaging in this behavior did not allow us to examine subgroup differences. Third, the cross-sectional design does not allow us to examine the temporality of substance use vis-à-vis the indicators of functioning. Finally, results from this study are based exclusively on self-reports of substance use and functioning, as external validation was not possible.

Results from this study indicate that one in five adults ages 30-80 engage in polysubstance use, especially a pattern involving heavy drinking combined with cigarette and cannabis use. This suggests that substance abuse treatment efforts for adults should involve screening for and addressing the possible use of multiple substances. Further, those who engage in polysubstance use may have competing unmet needs, such as poor mental health and weak social connections, that that require attention during treatment. Although this study provides an important first step in understanding patterns of substance use among adults, longitudinal research is needed to examine how these patterns may differentially affect functioning over time.

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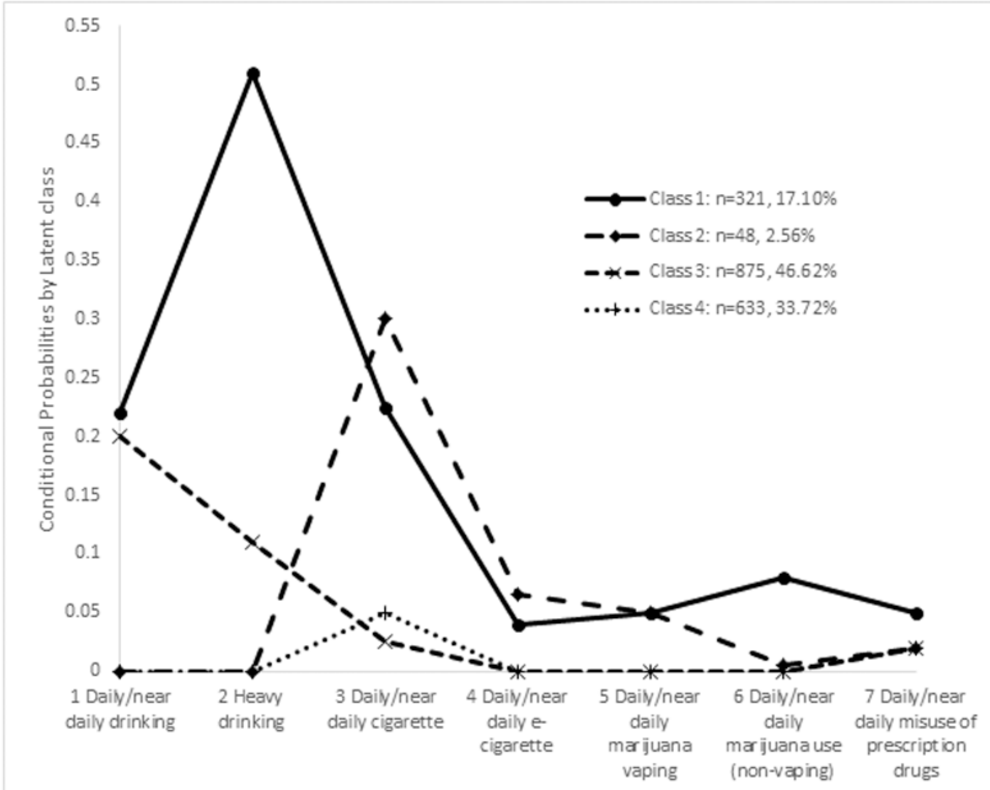

Figure 1:
Estimated conditional probabilities (Y-axis) of endorsing the highest category of each substance use item (daily/near daily or heavy use) for each latent class (plotted lines)

Table 1.

Information Criteria from LCA models extracting different number of classes

	2 classes	3 classes	4 classes	5 classes
Akaike (AIC)	9891.73	9495.59	9418.02	9357.38
Sample-Size Adjusted BIC (SABIC)	9979.07	9637.22	9613.93	9607.59
P value for Vuong-Lo-Mendell-Rubin likelihood ratio test[1]	.00	.00	.04	.92
P value for parametric bootstrap likelihood test[1,2]	N/A	N/A	.00	.00
Entropy	.99	.85	.84	.83

Notes.

[1]These two tests compare a model with K classes to a model with (K-1) classes.

[2]Some of the bootstrap draws did not converge, thus the results are not available. Although the 5-class vs. 4-class test result is significant ($p = .00$), the result from the Vuong-Lo-Mendell-Rubin likelihood ratio test is not ($p = .92$). Considering all this information collectively, we selected the 4-class solution as discussed in the Result section.

Table 2.

Latent Class Characterizations and Conditional Probabilities of Past Month Substance Use (*N* = 1,877)

	Class 1: Heavy Drinking, with Cigarettes/ Cannabis %	**Class 2: Cigarette Smoking, with Rx Drugs/ Cannabis %**	**Class 3: Lighter drinking %**	**Class 4: Abstaining %**
Class Prevalence	17.10	2.56	46.62	33.72
Any alcohol use				
No use	0	100	0	100
Non-daily use	77.99	0	80.89	0
Daily/almost daily use	22.01	0	19.11	0
Heavy alcohol use				
Non-drinker	0	100	0	100
Non-heavy drinker	42.59	0	88.49	0
Heavy drinker	57.41	0	11.51	0
Cigarette use				
No use	58.88	31.25	97.03	93.84
Non-daily use	13.40	35.42	1.37	0.79
Daily/almost daily use	27.73	33.33	1.60	5.37
E-cigarette use				
No use	86.60	77.08	99.66	99.53
Non-daily use	9.35	14.58	0	0
Daily/almost daily use	4.05	8.33	0.34	0.47
Cannabis use				
No use	65.42	66.67	97.03	97.95
Non-daily use	24.92	16.67	2.63	1.26
Daily/almost daily use	9.66	16.67	0.34	0.79
Cannabis vaping				
No use	79.44	85.42	100	99.68
Non-daily use	16.20	10.42	0	0
Daily/almost daily use	4.36	4.17	0	0.32
Nonmedical prescription drug use				
No use	90.03	58.33	98.74	98.74
Non-daily use	5.30	31.25	0.23	0
Daily/almost daily use	4.67	10.42	1.03	1.26

Notes. No use = 0 days; non-daily use = 1-19 days; daily/almost daily use = 20-30 days.

Table 3.

Comparing demographics and functionality across the latent classes

	Class 1: Heavy Drinking, with Cigarettes/ Cannabis	Class 2: Cigarette Smoking, with Rx Drugs/ Cannabis	Class 3: Lighter drinking	Class 4: Abstaining	Significant differences between the classes [a]
Demographics, %					
Male	46.73	35.42	45.37	35.70	1/4, 3/4
White	48.90	33.34	78.63	68.40	
Hispanic	29.60	18.75	10.17	15.17	
Black	15.89	33.33	6.51	11.53	
Other races	5.61	14.58	4.69	4.90	
Married	47.04	43.75	69.03	57.03	1/4
College degree	28.66	18.75	66.29	44.55	1/3, 1/4, 2/3, 3/4
Age 60+	16.20	18.75	54.06	48.34	1/3, 1/4, 2/3, 3/4
Income, %					1/3, 2/3, 2/4, 3/4
< $35,000	42.68	72.92	9.49	30.96	
$35,000-$59,999	26.17	8.33	20.57	27.18	
$60,000-$99,999	16.51	6.25	26.40	23.22	
$100,000 or more	14.64	12.50	43.54	18.64	
Social functioning, mean (SD) [b]					
Friend support	7.24 (2.51)	7.30 (2.63)	6.40 (2.23)	6.76 (2.56)	1/3, 1/4, 3/4
Family support	7.29 (2.69)	7.20 (3.06)	6.44 (2.50)	6.79 (2.79)	1/3, 1/4
Loneliness	5.10 (1.90)	5.34 (1.87)	4.33 (1.60)	4.79 (1.91)	1/3, 2/3, 3/4
Mental functioning, mean (SD) [b]					
Depression	4.75 (4.83)	7.64 (6.89)	3.30 (3.80)	4.51 (5.04)	1/2, 1/3, 2/3, 2/4, 3/4
Anxiety	4.19 (4.85)	6.81 (6.11)	2.63 (3.63)	3.36 (4.55)	1/2, 1/3, 2/3, 2/4, 3/4
Physical functioning, mean (SD) [b]	6.80 (5.20)	9.91 (6.04)	5.75 (3.91)	7.02 (4.91)	1/2, 1/3, 2/3, 2/4, 3/4

Notes.

[a] Pairs of class differences are indicated significant where $p < .05$.

[b] Higher score indicates worse functioning.

For demographic variables and the income variable, these are based on covariate effect on the latent classes using different reference groups. They are estimated as part of the model when defining the latent classes. For the measures of functioning, pairwise comparisons are made based on predefined latent classes.