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A Typology of Prescription Drug Misuse: A Latent Class Approach to Differences and Harms

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Abstract

Introduction and Aims—Prescription drug misuse is a considerable problem among young adults, and the identification of types of misuse among this population remains important for prevention and intervention efforts. We use Latent Class Analysis (LCA) to identify possible distinct latent groups of prescription drug misusers across multiple prescription drug types (pain killers, sedatives, and stimulants).

Design and Methods—Our data is comprised of a sample of 404 young adults recruited from nightlife scenes via time-space sampling. Through the specification of a zero-inflated Poisson Latent Class Analysis, we evaluate differences in class membership by various demographic factors as well as assess the relationship between class membership and health outcomes, including indications of dependence, problems associated with substance use, and mental health.

Results—Our assessment of fit indices led to a 4 class solution (dabblers, primary stimulant users, primary downers users, and extensive regulars). No demographic differences existed between latent classes. The extensive regular class report the greatest number of symptoms related to dependence, greatest number of problems related to misuse, and the greatest mental health problems. The dabblers report the fewest problems and symptoms, while the other two classes experiences problems and symptoms in between the classes on the extremes.

Discussion and Conclusions—Prevention efforts should take into account that young adults who misuse prescription drug have different profiles of misuse, and there may be a need for varied interventions to target these different types of misuse.

Keywords

prescription drug misuse; young adults; latent class analysis; risk; mental health

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Introduction

Globally, the misuse of prescription drugs – drugs obtained from a non-medical source or used for a non-medical or recreational purpose – grew considerably during the first decade of the 21st century [1–2], especially among young adults [3]. Elevated rates of misuse among young adults occur for a range of prescription drug classes, including pain killers, sedatives, and stimulants [4]. Given the scope of this trend, continued assessment of patterns of prescription drug misuse among young adults is critical to enable health promotion efforts. Accordingly, we aim to provide a typology of prescription drug misuse among young adults.

Although many studies of prescription drug misuse focus on those who misuse one particular drug type, many have a history of consuming more than one type of prescription drug non-medically. The use of multiple drugs or their combination – polydrug use – has been shown to elevate problem outcomes. Polydrug use is a common occurrence across many types of drugs [5–7], including prescription drugs [8–9]. It has been associated with a greater likelihood of overdose [10], higher odds of drug dependence [11], and psychiatric comorbidities [12]. Despite the risks posed by polydrug use and research suggesting that young people are likely to engage in polydrug use, this aspect of prescription drug misuse remains relatively understudied. A recent study of high school seniors reported that 70% of those who misused a prescription opioid in the last year had engaged in polydrug use [13]. A study in nightlife scenes indicated that 65.9% of those who misuse prescription drugs engaged in recent polydrug use [9]. The identification of differing patterns of prescription drug misuse among young adults and how these patterns shape health outcomes remains important to assist professionals working with this population.

Assessments of types of prescription drug misuse must also consider the factors that influence how these patterns differ, such as demographic characteristics. Prescription drug misuse has been shown to vary by gender, race/ethnicity, and sexual orientation, with the prevalence of prescription drug misuse higher among men [14], Whites [15–16], and sexual minorities [17]. These demographic differences have been found specifically among young adults [18–19]. Assessing differences in types of prescription drug misuse remains equally important; that is, understanding different patterns in the frequency of misuse of multiple prescription drugs will provide us with a fuller picture of this drug trend.

Current Study

We use Latent Class Analysis (LCA) to identify distinct latent groups of prescription drug misusers across multiple prescription drug types (pain killers, sedatives, and stimulants). LCA has increasingly been used to understand a range of substance use concerns, including different types of drugs, such as club drugs [20–21] and prescription drugs [22–23], and drug-related issues such as barriers to drug treatment [24]. Relative to variable-centered approaches that focus on relations among variables and assume a homogeneous population, LCA is a person-centered analytic approach through which we utilize mixture models to assess population heterogeneity and identify distinct subpopulations *a priori* unknown [25–28]. We evaluate differences in class membership by demographic factors and assess the relationship between class membership and health outcomes, including dependence, substance use problems, and mental health. The identification of these types may allow for targeted approaches to health promotion efforts.

Methods

Sampling

We utilized time-space sampling in venues that house nightlife scenes in New York, supplemented by online scene-targeted recruitment. Time-space sampling was developed to capture hard-to-reach populations [29–31], but is also constructive for generating samples of venue-based populations [32]. As young adults in nightlife scenes are a venue-based population, we used venues as our unit of sampling to generate a sample of socially active young adults. We sampled through randomizing 1) the venues attended and 2) the days and times we sampled individuals from them.

We randomized “time” and “space” using a sampling frame of venues and times of operation. To construct the sampling frame, ethnographic fieldwork enabled the assessment of viable venues for each day of the week. A venue was deemed viable if a threshold of young adult patron traffic existed on that given day. We generated lists of viable venues for each day of the week across several key scenes – electronic dance music (EDM), gay clubs, lesbian parties, indie rock, and the warehouse scene. Venues included bars, clubs, lounges, warehouses, and performance venues. For each day of the week, all viable venues were assigned a number. Using a random digit generator, a random number was drawn corresponding to a particular venue on a particular day. Ultimately, this process yielded our schedule of venues for each month. The recruitment occurred between 2011 and 2013.

Once at the venue, project staff used a brief survey to screen as many individuals as possible. They approached a patron, identified themselves, described the screening survey, and requested verbal consent for participation in the brief survey conducted on an iPod Touch®. For those who consented (75.0% of those approached), the first few questions were administered by trained staff (age and residency) and respondents self-reported more sensitive information (race, sexual orientation, gender, and substance use). Staff members were trained not to administer surveys to individuals visibly impaired by intoxication to ensure the capacity to consent.

If participants were eligible (9.4% of those screened), they were given a brief description of the study and asked to provide contact information if they were interested (77.4% of eligible individuals chose to do so). Later in the study timeline, recruiters provided eligible participants the opportunity to verify age and identity at the point of recruitment so the study assessment could be completed online. Near the end of the project, venue recruitment was supplemented by scene-targeted recruitment via online groups associated with nightlife scenes of interest (e.g. groups for EDM clubs or with interests in indie rock). The research team developed a list of groups relevant to the scenes of interest. Group members between the ages of 18–29 who resided in the metropolitan area saw an advertisement for the study; if they clicked on the advertisement, they were directed to a screening survey and, if eligible, collected their contact information. Less than 5% of the sample was recruited via this supplemental method, and all completed the survey assessment at the community-based research office to ensure age and residence eligibility.

All participants were contacted by phone and e-mail so that staff could provide more information about the study, confirm eligibility, and schedule the assessment. Eligibility criteria were: 1) Aged 18–29; 2) Reported the misuse of prescription drugs at least three times in the past six months; and 3) Reported the misuse of prescription drugs during the past three months. In their initial assessment, participants completed the informed consent process, then completed the survey – via ACASI for those who completed the assessment at the community-based research office (n=269) and via Qualtrics® for the online assessments (n=135). The survey took approximately one hour to complete and, once completed, participants were compensated $50 in cash, check, or gift card (depending on their preference). All procedures were reviewed and approved by the universities' Institutional Review Boards.

Measures

Demographics—Participants self-reported their age, gender, sexual identity (gay, straight, bisexual, queer, or questioning), race/ethnicity (White, Black, Latino, Asian/Pacific Islander, or mixed), highest education completed (some high school, high school diploma, some college, currently enrolled in college, 4-year college degree, or graduate school), parental socio-economic status (poor, working class, middle class, upper middle class, or wealthy), and employment status (full-time work, part-time work, part-time work/student, unemployed student, or unemployed).

Prescription Drug Misuse—This project used the following operational definition of prescription drug misuse, which was provided to subjects: "…using prescription drugs obtained from a non-medical source, using more than the prescribed dose, or using prescription drugs for a non-medical or recreational purpose." Respondents reported lifetime use and their frequency of misuse during the previous three months.

Correlates of Harm—Respondents self-reported whether they had misused prescription drugs through sniffing, smoking, or injecting routes of administration. Studies have suggested that transitions to other routes of administration indicate an escalation of drug use [33]. The Composite International Diagnostic Interview (CIDI) Substance Abuse Module was tailored to assess symptoms of drug dependence related to prescription drug misuse [34]. This 8-item measure is widely used to assess symptoms of drug dependence. The Short Inventory of Problems with Alcohol and Drugs (SIP-AD), a 15-item inventory of problems associated with substance use, was tailored to assess problems associated with the misuse of prescription drugs [35]. The Alcohol Use Disorders Identification Test (AUDIT), an internationally recognized measure of problem drinking, was used to assess problem drinking [36]. The BSI-18 was used to capture symptoms of mental health problems over three domains (depression, anxiety, and somatization) using the domain specific subscales. The BSI-18 is a strong measure of mental health symptoms among people who use drugs [37]. Stress and coping were measured using the Rhode Island Stress and Coping Inventory

(RISCI). The RISCI contains a 7-item subscale measuring stress during the past month and a 5-item subscale measuring coping. It has demonstrated strong reliability and validity [38].

Statistical Analyses

We utilized latent class analysis in *Mplus* version 7.11 [28] to empirically investigate and delineate groups of individuals based on their frequency of prescription drug misuse during the prior three months. Specifically, we entered the number of days on which participants used prescription stimulants, pain killers, and sedatives. Because these variables were counts and there was a preponderance of zeroes for each variable, we specified a zero-inflated Poisson (ZIP) LCA. The ZIP model is a two-part model that simultaneously models both a binary and a count function. The ZIP model incorporates zeros into both the binary – in which it attempts to predict true zeros (i.e., inflation) – as well as the count portions of the model [39]. We freed the inflation parameters to vary across classes. LCA can be delineated from factor analysis by its person-centered approach. Considered in the context of substance use, factor analysis would attempt to identify distinct *subtypes of drugs* based on their profiles of use *across all individuals*, whereas LCA attempts to identify distinct *subtypes of individuals* based on their profiles of use *across drugs*.

We performed the analysis iteratively from two- through seven-class models and compared the models utilizing several available fit indices. Specifically, the Akaike's Information Criteria (AIC), Bayesian Information Criteria (BIC), and Adjusted BIC (ABIC) fit indices were used in combination with the model fit based on the likelihood chi-square statistic, the model's entropy, the Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT), the bootstrapped likelihood ratio test (BLRT), and the interpretability and size of the classes to determine the best fitting model. Lower values of the AIC, BIC, and ABIC demonstrate better fit and higher values of entropy – which ranges from 0 to 1 – indicate better precision in class assignment and greater class separation [26]. Non-significant chi-square statistics for the model fit suggest that it is not significantly different from a saturated model and provides adequate fit, and significant LMR-LRT and BLRT statistics suggest that the model is a significant improvement from a model with one fewer class (i.e., the $k - 1$ model) [26, 40–41]. To improve estimation, we increased several of the random start features in *Mplus* (STARTS = 600 40; STITERATIONS = 40; K-1STARTS = 600 40; LRTSTARTS = 600 40).

Upon selecting a final latent class solution, we used the most likely class membership for each participant to conduct chi-squared tests and analysis of variance (ANOVA) to examine differences in the latent classes by demographic characteristics as well as severity of substance use. In ANOVA, we requested post-hoc tests using LSD adjustment.

Results

Table 1 displays the demographic characteristics of the sample. One-third of the sample were racial minorities. The sample, by design, was relatively evenly split with regards to gender and sexual orientation. Slightly less than half of the sample was partnered. More than half had a 4-year college degree. The sample was diverse with regards to parental SES.

Nearly half made less than $20,000 per year at the time of enrollment. The sample was diverse with regard to employment status.

We also provide substance use characteristics of the sample within Table 2. These characteristics include lifetime use of eleven substances, the recent use of these substances, and the number of days within the past 3 months on which the substance has been used among those who recently used. The lifetime prevalence for alcohol, marijuana, MDMA, and cocaine was quite high, and recent use of these substances also occurred among considerable proportions of the sample. Other drugs such as heroin, methamphetamine, ketamine, and other prescription drugs were used by less of the sample; however, those who did use these substances did so relatively frequently.

Latent class results

The model fit information for each of the six models tested is presented in Table 3. As is common in LCA, we based our identification of the best fitting class on both statistical properties of the models as well as conceptual interpretability [26]. Based on the results, we ultimately selected a model with a four-class solution. Initial fit indices suggested that the three-class solution was a significant improvement upon the two-class solution. Although the LRT suggested that a four-class solution was not a significant improvement from the three-class solution, other fit indices (e.g., AIC, BIC, ABIC) suggested the four-class solution had a better fit. We found that the four-class solution extracted a meaningful fourth class (the "*extensive regulars*" described below) that were conflated with and changed the meaning of two other classes ("*primary stimulants*" and "*primary downers*") in the three-class solution. The average probability of most likely latent class membership was high across classes and ranged from 93.3% to 99.9%. Models with larger numbers of classes had less interpretable classes with some classes being particularly small without any substantial improvement in model fit. In particular, the fit indices for 5-class solution are not appreciably different from those of the 4-class solution. For this reason, the more parsimonious 4-class solution was selected. Table 1 displays a comparison of the four classes on demographic characteristics. As can be seen, the four classes did not differ significantly on any of the demographic variables of interest

There were clear differences across the latent classes. Figure 1 displays the average frequency of each drug for each of the four classes. The first class accounted for 6.7% of the sample and consisted of individuals who had high levels of use across all three categories of prescription drugs ('*extensive regulars*'). The second class accounted for 56.7% of the sample and contained individuals who, on average, had low levels of use across all three categories of prescription drugs ('*dabblers*'). The third class (14.4% of the sample) and fourth class (22.2% of the sample) contained individuals who primarily used "*downers*" (i.e., pain killers and sedatives) and "*stimulants*," respectively. The probability of true zeros was 0.28 for stimulants, 0.29 for pain killers, and 0.25 for sedatives for the first class, 0.33, 0.30, and 0.14 for the second class, 0.28, 0.30, and 0.18 for the third class, and 0.39, 0.27, and 0.34 for the fourth class.

In the final set of analyses, we compared the four classes on their severity of substance use and mental health problems. As can be seen in Table 4, the four groups all differed significantly from each other on both the CIDI and the SIP-AD. Specifically, the dabblers had the lowest score on both measures, the primary stimulant users had the next highest score, followed by the primary downers users, and the extensive regulars had the highest scores on both measures. With regard to the BSI subscales, the extensive regulars reported significantly higher scores for somatization, depression, and anxiety, suggesting high levels of mental health difficulties among this group compared with the other three groups. The dabblers reported significantly lower prevalence of non-oral modes of administration of prescription drugs compared to the other three groups. No significant group differences emerged when analyzing the AUDIT scores or RISCI scales.

Discussion

The results of our LCA identified four types among young adults who misuse prescription drugs, and as such we provide evidence for the clustering of patterns of prescription drug misuse. In many respects, these analyses verify what we should expect, namely that those who more frequently misuse multiple prescription drug types experience a greater degree of problems associated with their use. Yet, we did not identify any demographic patterning of class membership. Nonetheless, these findings have varying implications for addressing the issue of prescription drug misuse among young adults.

Dabblers comprise the largest class. The typical young adult in this class misuses prescription drugs of any type in approximately monthly intervals; such intermittent misusers may be experimenting or misusing for infrequent instrumental purposes. Typical members of the primary stimulant class have regular patterns of stimulant use, greater than weekly use, but infrequently use other types of prescription drugs. Such a type may be primarily motivated by the task-specific uses for stimulants or to stay awake and maintain energy while involved in nightlife. The typical member of the primary downers class regularly uses both sedatives and pain killers on a frequent, though not daily, basis; yet, such individuals rarely use stimulant drugs. The typical young adult in the extensive regulars class engages in frequent use of all types of prescription drugs. These individuals demonstrate more habitual patterns of use.

It is noteworthy that we did not find any differences in class membership on the basis of individual demographic characteristics. Previous studies have shown that gender [14–19], race/ethnicity [15–16], and sexual orientation [17–18] influence individual odds of prescription drug misuse. Yet, our findings indicate that once individuals are misusing prescription drugs, these factors do not influence the type of prescription drug misuse they eventually engage in.

While we found no demographic differences, our typology of prescription drug misuse did identify differing risk profiles between the classes. As described above, those in the extensive regulars class report the greatest number of symptoms related to dependence and greatest number of problems related to prescription drug misuse. The dabblers report the fewest. With respect to the groups that fall in between, it is noteworthy that individuals in the primary downers class report greater symptoms of dependence and greater problems than those in the primary stimulant class. This may relate directly to a greater addiction liability of opiates and benzodiazepines. Those in the extensive regulars class report considerably greater mental health symptoms for depression, anxiety, and somatization. While it remains unclear whether the mental health symptoms precede or result from prescription drug misuse, young adults who heavily use a number of prescription drug types merit attention for their accompanying mental health concerns. Finally, the results indicate that a greater proportion of those who regularly misuse prescription drugs of any class proceed to escalate their misuse by engaging in non-oral modes of administrating these drugs. Thus, as might be expected, the regular misuse of prescription drugs may open pathways for escalating misuse through routes that provide more efficient highs.

Limitations

Although we have identified an important typology of prescription drug misuse and the risks related to these classes, we must consider some limitations. First, this project was designed to study young adults involved in nightlife scenes. This population is important to study due to the salient role that substances play in nightlife venues, yet these findings may not generalize to the entire young adult population. The methods here, however, allow for us to identify types of misuse within an at risk population. Second, as we sampled from nightlife venues using time-space sampling, we may have been more likely to screen people who are more frequent nightlife participants; as is the case with active venue-based recruitment strategies, those who go out more often are more likely to encounter recruitment staff by virtue of being present more often. Finally, as subjects self-reported behaviors, there may be social desirability bias in the reporting of some behaviors, as is common in such studies. However, the use of computer-assisted surveys improves self-report measures of sensitive topics, [42–43] which improves our confidence in these responses.

Conclusions

Our findings indicate four types of young adults who misuse prescription drugs. Prevention efforts should take into account that young adults who misuse prescription drugs have different profiles of misuse, and there may be a need for varied interventions to target these different types of misuse and the varying motivations that underlie differing patterns of use. In particular, young adults who regularly misuse an extensive range of prescription drugs demonstrate a significant need for intervention on both substance abuse and mental health. Some of these individuals may clinically present symptoms for dual diagnosis. While no demographic factors are related to membership in any class of misuse, the classes are differentially associated with adverse drug-related outcomes, such as social problems, symptoms of dependence, and symptoms of mental health disorders. Further research into the longitudinal trajectories of each type of prescription drug misuse is needed, as such research may assist with the identification of individuals with the greatest vulnerability for transitioning to heavy patterns of misuse and the heightened risks associated with it.

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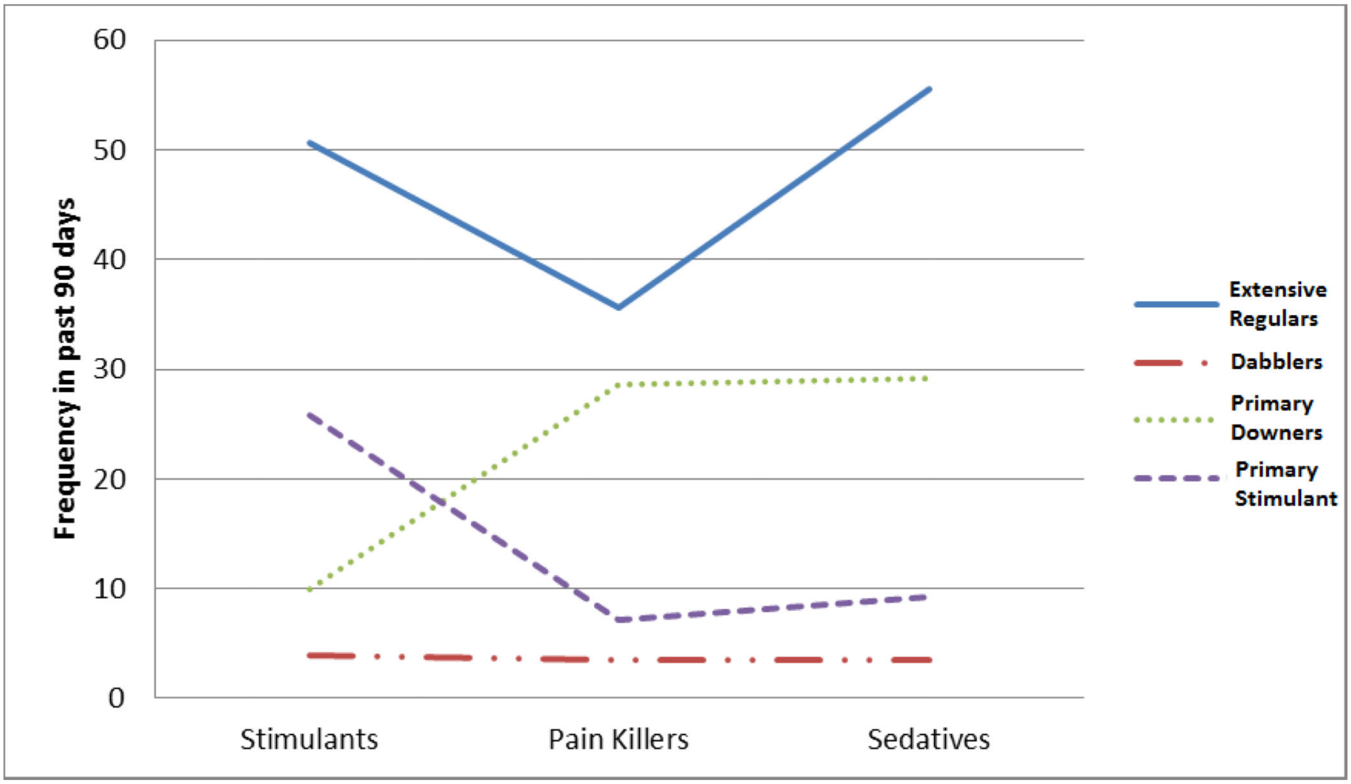

Figure 1.
Recent frequency of prescription drug misuse by latent class

Table 1

Demographic information and comparisons by latent class membership.

	Full Sample (N = 404)		Latent Class Comparisons: Dabblers (n = 229)		Primary Stimulant (n = 90)		Primary Downers (n = 58)		Extensive Regulars (n = 27)		
Demographic Characteristics	***n***	**%**	***n***	**%**	***n***	**%**	***n***	**%**	***n***	**%**	**Test Statistic**
Race/Ethnicity											$\chi^2(3) = 2.50$, *ns*
White	270	66.8	159	69.4	60	66.7	35	60.3	16	59.3	
Non-White	134	33.2	70	30.6	30	33.3	23	39.7	11	40.7	
Gender											$\chi^2(9) = 13.19$, *ns*
LGBQ Male	113	28.0	74	32.3	17	18.9	14	24.1	8	29.6	
Straight Male	108	26.7	52	22.7	28	31.1	21	36.2	7	25.9	
LGBQ Female	81	20.0	46	20.1	16	17.8	14	24.1	5	18.5	
Straight Female	102	25.2	57	24.9	29	32.2	9	15.5	7	25.9	
Relationship Status											$\chi^2(3) = 1.19$, *ns*
Single	225	55.7	128	55.9	49	54.4	35	60.3	13	48.1	
Partnered	179	44.3	101	44.1	41	45.6	23	39.7	14	51.9	
Education											$\chi^2(3) = 1.63$, *ns*
Less than 4-year degree	176	43.6	97	42.4	37	41.1	28	48.3	14	51.9	
4-year degree or higher	228	56.4	132	57.6	53	58.9	30	51.7	13	48.1	
Parental Socioeconomic Status[1]											$\chi^2(6) = 5.03$, *ns*
Poor or working class	92	22.9	48	21.1	25	28.1	14	24.1	5	18.5	
Middle class	157	39.2	98	43.2	29	32.6	21	36.3	9	33.3	
Upper middle class or rich	152	37.9	81	35.7	35	39.3	23	39.7	13	48.1	
Current Income[2]											$\chi^2(6) = 2.55$, *ns*
Less than $20k per year	194	49.4	111	49.8	39	44.3	329	51.8	15	57.7	
$20k to $39.9k per year	109	27.7	63	28.3	25	28.4	14	25.0	7	26.9	
$40k per year or more	90	22.9	49	22.0	24	27.3	13	23.2	4	15.4	
Employment Status											$\chi^2(6) = 6.56$, *ns*
Unemployed	84	20.8	44	19.2	17	18.9	14	24.1	9	33.3	

	Full Sample (N = 404)		Latent Class Comparisons: Dabblers (n = 229)		Primary Stimulant (n = 90)		Primary Downers (n = 58)		Extensive Regulars (n = 27)		
Demographic Characteristics	***n***	**%**	***n***	**%**	***n***	**%**	***n***	**%**	***n***	**%**	**Test Statistic**
Part-time employment	162	40.1	91	39.7	36	40.0	22	37.9	13	48.1	
Full-time employment	158	39.1	94	41.0	37	41.1	22	37.9	5	18.5	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	Test Statistic
Age	24.6	2.7	24.5	2.8	24.7	2.6	24.6	2.7	25.0	1.9	$F(3, 400) = 0.34$, *ns*

Note.

[1] Three participants did not report parental class background.

[2] 11 participants did not report current income.

Table 2

Substance Use Characteristics among Participants

Substance	**Lifetime Use**	**Any use during past 3 months**	**Mean # of days in past 3 months (among those who currently use)**
Alcohol	99.8%	99.3%	47.2
Marijuana	99.3%	89.1%	37.9
Rx pain killers	91.6%	70.8%	14.2
Rx sedatives	90.3%	74.3%	16.1
Rx stimulants	90.8%	69.1%	18.7
Other Rx drug misuse	30.0%	12.9%	41.3
Ecstasy	80.2%	45.8%	6.7
Methamphetamine	16.1%	2.5%	15.4
Ketamine	33.2%	10.9%	7.3
Cocaine	81.1%	57.4%	11.6
Heroin	16.6%	5.0%	38.5

Table 3

Model fit comparisons for two through seven latent classes.

Model Fit	Number of Latent Classes					
	2	**3**	**4**	**5**	**6**	**7**
AIC	13718.377	11714.888	10631.789	9882.900	9333.519	8991.051
BIC	13770.395	11794.916	10739.827	10018.948	9497.577	9183.118
ABIC	13729.145	11731.454	10654.153	9911.062	9367.479	9030.809
Entropy	0.983	0.948	0.942	0.940	0.923	0.926
LR χ^2 p-value	0.300	0.279	0.028	0.048	0.649	0.961
LRT p-value	0.000	0.027	0.434	0.283	0.121	0.244
BLRT p-value	0.000	0.000	0.000	0.000	0.000	0.000

Table 4

Differences in substance use severity, mental health, and route of administration by latent class membership.

	Full Sample (N = 404)		Latent Class Comparisons: Dabblers (n = 229)		Primary Stimulants (n = 90)		Primary Downers (n = 58)		Extensive Regulars (n = 27)		
	M	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	**Test Statistic**
CIDI Score	2.24	2.23	1.54[a]	1.96	2.52[b]	2.13	3.53[c]	2.19	4.37[c]	2.10	$F(3, 400) = 27.10^{***}$
SIP-AD Score	5.01	6.63	3.02[a]	4.11	5.42[b]	6.33	8.40[c]	7.73	13.26[d]	11.56	$F(3, 400) = 31.91^{***}$
AUDIT Score	13.10	6.76	13.25	6.74	13.21	6.17	11.90	6.43	14.04	9.22	$F(3, 400) = 0.83$
BSI Somatization	3.96	3.92	3.58[a]	3.65	3.67[a]	3.97	4.45[a]	3.26	7.15[b]	5.65	$F(3, 400) = 7.47^{***}$
BSI Depression	6.25	5.51	5.83[a]	5.41	6.39[a]	5.56	5.97[a]	4.86	10.00[b]	6.28	$F(3, 400) = 4.83$**
BSI Anxiety	6.18	4.98	5.61[a]	4.89	6.02[a]	4.42	6.71[a]	4.62	10.44[b]	6.14	$F(3, 400) = 8.29^{***}$
RISCI Stress	22.36	5.63	22.41	5.54	21.91	5.54	21.7	5.78	24.89	5.91	$F(3, 400) = 2.31$
RISCI Coping	18.98	3.52	19.08	3.40	19.01	3.54	19.26	3.36	17.44	4.48	$F(3, 400) = 1.91$
	N	%	*n*	%	*n*	%	*n*	%	*n*	%	
Non-Oral Admin of Rx	155	38.4	73	31.9[a]	39	43.8[b]	29	50.0[b]	14	51.9[b]	$\chi^2(3) = 10.58^{*}$

Note.

$^{*}p \leq .05$.

$^{***}p \leq .001$.

Means with different superscripts differed significantly at $p < .05$ or less in LSD post-hoc tests. Percentages with different superscripts differed significantly at $p < .05$ or less in post-hoc tests.