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Typologies of Recanting of Lifetime Cigarette, Alcohol and Marijuana Use During a Six Year Longitudinal Panel Study

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Abstract

AIM—To identify if there are different typologies for adolescent self-reporters and recanters for alcohol, cigarette and marijuana use.

METHODS—This study is a secondary data analysis and utilized four waves the National Longitudinal Survey of Youth child panel data. The study included adolescents aged ten and older who self-reported ever use of cigarettes (N=872), marijuana (N=854) or alcohol (N=837). Consistent responders were those who reported lifetime use of a specific substance and continued to report such use at each latter wave of data collection. Latent class analyses were utilized to investigate if there are different types of self-reporters for each substance class.

RESULTS—Three unique groups for each substance was identified. The first group of users, who had a late age of onset, tended to be consistent self-reporters across waves. Those who were early onset users of cigarettes and marijuana tended to recant their use while early onset alcohol users were consistent reporters. Those with moderate ages of onset had no consistent recanting patterns. The highest degree of recanting was found among the early onset marijuana users.

CONCLUSIONS—The results suggest that youth who begin their use at an earlier age may not be as reliable reporters as youth who initiate use at later ages. Our results suggest the veracity of prevalence estimates for licit and illicit substances could be different depending on the age of the respondent.

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Contributors

Drs. Shillington, Clapp and Reed designed the study and wrote the protocol. Dr. Shillington wrote the Background section. Dr. Roesch undertook the statistical analysis, and wrote the first draft of the methods and results. Drs. Reed and Woodruff contributed to the analysis plan. Drs. Clapp and Reed contributed to the discussion section. All authors contributed to and have approved the final manuscript.

Conflict of Interest

(mandatory). All authors declare that they have no conflicts of interest.

1.0 INTRODUCTION

Most of the data on national trends, prevalence and incidence of adolescent substance use employ self-reports. Concern regarding the validity and stability of self-reported substance use has resulted in a number of publications on this topic. Such research has examined consistency in self-reported lifetime substance use among adults (Fendrich and Vaughn, 1994; Fendrich and Mackesy-Amiti, 1995; Johnston and O'Malley, 1997; Fendrich and Kim, 2001) and adolescents (O'Malley et al., 1983; Barnea and Teichman,1987; Bailey et al.,1992; Smith et al., 1995; Johnson and Mott, 2001; Fendrich and Rosenbaum, 2003; Golub et al., 2000a; Golub el., 2000b; Shillington et al., 2000). The impact of self-report data on the science of substance abuse prevention and treatment is considerable.

Rice and colleagues (1992) discuss a paradigm to test-retest reliability, which is a test of temporal stability. Temporal stability requires that two interviews be conducted and spaced far apart in time to determine how well respondents repeat their answers from one interview to another. The questions are necessarily questions for which the answers should not waver. For example, once one has reported lifetime use of alcohol, then all replies to that question should always be affirmative. Unlike the short temporal interval employed in test-retest reliability analyses, measures in stability studies are typically conducted one year or more after the initial survey period. The underlying assumption of the concept of stability is that if one reports use at time 1, then lifetime use should be reported by the same respondent at every subsequent measurement period. Where test-retest reliability is aimed at measuring the potential error in a measure (Pedhazur and Schmelkin, 1991), stability is focused more on participant recall errors.

Fendrich and Rosenbaum (2003) reported recanting rates (reporting use at time 1 but denying use at time 2) of 45% for alcohol use and about 50% for cigarette use among teens in a longitudinal study examining the effectiveness of the DARE program. Siddiqui and colleagues (1999) found a 24% report inconsistency rate for at least one substance. Johnson et al. (1997) found a 25% decrease in reported alcohol incidence and an 18% decrease in reported marijuana incidence over a five-year time span. Fendrich and Kim (2001) examined adult recanting with a longitudinal design in 1988, 1992, and 1994. Specifically, they found 40% of cocaine users and 30% of marijuana users denied use in at least one follow-up period after prior reports of use.

Shillington and colleagues (2010) have investigated the report stability of adolescent cigarette, alcohol and marijuana use using two-year, wave-to-wave comparisons of data from the NLSY. Results indicated that from 1988–98, between 67%–83% of adolescent users had report stability for cigarette use, Similarly, those reporting lifetime alcohol use, wave-to-wave from 1988–98, had report stability ranging from 65%–85% (Shillington et al., in press). The same analyses for marijuana use revealed report stability, from 1992–98, of 73%–81% (Shillington et al., in press). Thus the recanting rates fluctuated between 15% – 35% based upon the substance and the wave-to-wave comparison under study.

Although there are a number of studies that have examined report stability over two-year time periods, to date, no study has examined report stability for adolescent substance use longitudinally with the primary aim of identifying typologies of reporters using a person-centered analytical approach or latent class analysis. Although there have been prior studies that have used latent class analysis within cross-sectional data, they have examined the error within a specific survey, comparing self-reports against a gold standard (Berzofsky et al., 2008; Kreuter et al., 2008; Biemer and Wiesen, 2002). However, this study's approach is somewhat different; it uses latent class analysis.

In order to examine changes in self-reported substance use across time with a panel study design, these analyses are longitudinal instead of cross-sectional and we examine consistencies of an individual's repeated self-reports to the same question rather than using a gold standard. The purpose of this study will be to longitudinally examine whether there are different typologies of self-reporters for cigarette, alcohol and marijuana use.

2.0 METHODS

2.1 Data source

The National Longitudinal Survey of Youth (NLSY) is conducted in the U.S. and uses a multistage stratified random sampling technique. Originally, beginning in 1979, 5,828 females and 5,578 males, were interviewed with an over-sampling of Blacks and Hispanics. This panel study interviewed the participants annually with a retention rate at the twelve-year follow-up of 90.5% (Baker et al., 1993). Beginning in 1986, the study expanded to include the children of the female respondents. These children, however, were born to young mothers and therefore are not a nationally representative sample of children.

When the children reached age ten they were asked to complete a self-report instrument entitled the Child Self Administered Supplement (CSAS). This instrument queried areas such as attitudes, substance use, religiosity, deviance, and child-parent relationships. The interviews of the children have been conducted every two years. In 1994, a new measure was introduced. While children aged 10–14 still completed the CSAS, the new measure was utilized by those 15 years and older. The new survey was entitled the Young Adult Survey (YAS). The YAS asked about cigarette, alcohol and other substance use, sexual activity, delinquent activities and relationships.

Across the surveys, many children aged out of the CSAS and started responding to the YAS. Although the responses to the individual substance use questions were sometimes from the two different surveys, the questions that queried use are nearly the same within each wave. For most waves of data, a respondent would answer a question asking if they "ever used" a specific substance (no or yes). However, there were 1–2 waves of data collection (depending on whether it was the CSAS or YAS) during which the youth was asked to respond to a question regarding the number of times they had used a particular substance. If a youth reported "0" for the number of times of marijuana use, he/she was coded as "no" for lifetime use, and if he/she reported 1 or more, the code was a "1" for "yes" to lifetime use.

For the purposes of this study, we included adolescents who had complete data for all four waves under analysis: 1992, 1994, 1996 and 1998. The age ranges for each of the four waves was 10–16 in 1992, 12–18 in 1994, 14–20 in 1996 and 16–22 by 1998. The sample was 50.7% male and ethnically diverse with an over representation of Blacks (35.3%) and Hispanics (22.2%). Across the four waves included in this study, the prevalence of ever use of cigarettes ranged from 19–32%, for marijuana use it was 4–19% and alcohol it was 25–38%.

2.2 Measurement

Variables for ever-use for each substance studied were merged using the CSAS and the YAS. The variables utilized were the lifetime "ever-use" questions that queried cigarette use, alcohol use, and marijuana use at each wave of data collection for 1992, 1994, 1996 and 1998. Any youth who reported "yes" to any lifetime question for each substance during those four waves were included for these analyses. The ever-use sample having complete data for all four waves of data collection was: cigarettes, *n*=872; marijuana *n*=854; and alcohol *n*=837.

2.3 Statistical analysis

For the analyses in this paper, MPlus 6.0 was used (Muthen and Muthen, 2006). Latent class analysis (LCA) is person-centered statistical approach that classifies individuals into groups based on their patterns of responses to sets of observed variables (see McCuthcheon,1987; Lanza et al., 2003; Lanza and Collins, 2008 for a more technical description of these techniques). The primary goal is to maximize the *homogeneity* within groups (i.e., individuals within a class/profile should look similar) and maximize the *heterogeneity* between groups (i.e., individuals between classes/profile groups should look different). These groups, then, are represented by a categorical latent variable, as these groups are not directly known but are inferred from the response patterns on observed variables. For the present LCA analysis, the observed variables are binary/dichotomous (e.g., ever used cigarettes [0=no, 1=yes]).

To determine the *optimal* number of classes/profiles (referred to as class enumeration) requires the specification and testing of multiple class solutions (one-class, two-class, three-class, etc.). From these models, the designation of the “best-fitting” model is determined using a variety of statistical indicators. The Lo-Mendell-Ruben Adjusted Likelihood Ratio Test (LMRT) was developed as an inferential statistical test to determine model fit (Lo et al., 2001). The LMRT provides an indication of statistically significant improvement in fit for a model with *k* latent classes/profiles as compared to a model with *k-1* latent classes/profiles by approximating the differences between two log likelihood values (instead of using the $|\chi^2$ distribution). Thus, a significant LMRT test indicates that a more complex model (e.g., three-class) provides superior fit to a less complex model (e.g., two-class). A number of fit indicators based on information criteria have also been employed, and include the Akaike Information Critreria (AIC) (Akaike, 1974), the Bayesian Information Criterion (BIC) (Schwarz, 1978), and the sample size-adjusted BIC (sBIC) (Sclove, 1987); each of these information criteria is based on the log likelihood function for individual models (rather than comparing two log likelihood values as the LMRT does). All three statistical indicators penalize models for estimating too many parameters; moreover, both versions of the BIC further penalize models by sample size. None of these information criteria can determine model fit for the evaluation of individual models in isolation. A determination of the best-fitting class/profile solution, then, is based on which model has lower values for these fit indicators (lower values indicates better relative fit). 1

An underused statistical indicator of class enumeration is entropy (Ramaswamy et al., 1993). Entropy is a measure of how well classes or profiles can be distinguished or the percentage of individuals in the sample that were correctly classified given the specific class model. In contrast to other statistical grouping approaches like cluster analysis, individuals in LCA are assigned a *posterior probability* for each class/profile rather than outright assigned to one and only one class/profile. These posterior probabilities are a function of each individual’s response pattern, the number of latent classes/profiles, and the proportion of individuals estimated to be in each class/profile. So, for example, assume we are statistically evaluating a three-class model: an individual would have a posterior probability for class/profile one (e.g., .65), class/profile two (e.g., .25), and class/profile three (e.g., .10). Because the posterior probability for this individual is highest in class/profile 1, they would be “assigned” to that class. However, the flexibility of LCA accounts for the likelihood that

[1]Statistical indicators of overall model fit (e.g., BIC) are based on likelihood functions. The mathematical goal of these functions is to identify the most accurate solution/model (referred to as the global solution). However, LCA models in general are known to have likelihood functions that perform erratically (referred to as local optima). These local optima then can erroneously identify the “best” solution. To overcome this, programs such as MPlus evaluate models with multiple sets of starting values to help determine if the global likelihood can be replicated, and thus indicate the correct class/profile solution. In the current study, the STARTS option was used in MPlus, with 100 random sets of starting values used to generate the number of initial optimizations to use and 10 for the final optimizations.

there is uncertainty in class/profile membership. Entropy, then, is the aggregate of these posterior probabilities, with values greater than 80% considered noteworthy (Ramaswamy et al., 1993).

To further aid in the determination of the optimal number of classes/profiles, the interpretability of each class or profile must be considered. When evaluating the numerous statistical indicators identified above, it is quite common that inconsistencies in determining which class/profile solution fits best will occur. Thus, the interpretability of each class/profile could facilitate the determination of whether or not a specific class solution is more consistent with past theory and empirical research. There are two primary model parameters that are useful in this regard: (1) conditional response probabilities (CRP) and (2) latent class probabilities (LCP). CRPs are analogous to factor loadings (Lanza and Collins, 2008). CRPs refer to the probability for each observed variable *within* a latent class being present; for example, a CRP value of .90 in class one would reflect that 90% of the individuals within this class indicated *yes* for ever using cigarettes. These classes/profiles, then, are substantively characterized by interpreting responses within and between classes. For example, CRP values in a specific class of 1.00, .25, .20, and .15 for the ever-use cigarette variable across four time-points would indicate that everyone in the class responded *yes* to the variable at the first time-point but the majority said *no* at subsequent time-points, indicative of a recanting class.

LCPs indicate the prevalence of each case in a class (Lanza and Collins, 2008). Once classes/profiles are substantively interpreted, the probability or the proportion of cases within each class/profile helps identify the prevalence of class/profile membership. For example, we found LCP values for .80 for a never-use class (e.g., never used cigarettes at all time-points), .15 for an ever-use class at all time-points, and .05 for a recanter class (e.g., a class where individuals have responded *yes* to the ever use item at an earlier time-point followed by a *no* response at a subsequent, later time-point).

3.0 RESULTS

The observed variables used for these repeated measure LCAs were the binary indicators of *ever use* for cigarettes (*n*=872), marijuana (*n*=854), and alcohol (*n*=837), respectively, for years 1992, 1994, 1996, 1998. The sample sizes reflect complete data at each time-point for the target substance. Each substance was evaluated in an individual set of LCAs that tested 2–4 class solutions.

For ever-use of cigarettes, overall model fit information is presented in Table 1. The three-class solution was chosen as the best-fitting model primarily based on the statistical significance of the LMRT, high entropy value, and small differences in AIC and sBIC values versus the two- and four-class solutions. Latent class probabilities (LCP) for each class, an indicator of class size, were as follows: class one (LCP = .27), class two (LCP = .30), and class three (LCP = .43). The conditional response probabilities (CRP) for saying *yes* to the ever-use variable are presented in Table 2 and Figure 1. Class one is a high ever-use class; approximately half this class had reported that they had used cigarettes in 1992 with increasingly higher probabilities at the subsequent 3 time-points. However, reductions in the probabilities in years 1996 and 1998 relative to 1994 suggests that this class is also comprised of some recanters. Class two is an increasing ever-used cigarette class. The CRPS increased consistently across time, although a smaller number of individuals said *yes* to ever-use of cigarettes in 1992 (CRP = .09) than said *yes* in 1994, again suggesting some recanters in this class. Class three is a low use group. There does appear to be some recanters in this group, as well, since the CRP was reduced from .12 in 1996 to .00 in 1998.

For ever-use of marijuana, overall model fit information is presented in Table 3. The three-class solution was chosen as the best-fitting model primarily based on the statistical significance of the LMRT, high entropy value, higher sBIC relative to the other class solutions. LCPs for each class were as follows: class one (LCP = .74), class two (LCP = .15), and class three (LCP = .10). The CRP for saying *yes* to the ever-use variable are presented in Table 4. Class one, the largest class by far, is no- to little-use class across time, as CRPs were all relatively low, but did increase across the 4 time-points (Figure 2). Class two is an initial low-use class with dramatic increases in *yes* responses at the later two time-points. Class three can be considered a recanters class with increases in *yes* responses from 1992 to 1994 (CRP = 1.00 in 1994), but then reductions in *yes* responses at the later two time-points (.72 and .67, respectively).

When examining ever-use of alcohol, the overall model fit information is presented in Table 5. The 3-class solution was chosen as the best-fitting model primarily based on the statistical significance of the LMRT, higher AIC, and higher sBIC relative to the other class solutions. LCPs for each class were as follows: class one (LCP = .29), class two (LCP = .31), and class three (LCP = .40). The CRP for saying *yes* to the ever-use variable are presented in Table 6 and in Figure 3. Class one is a high ever-use class. Approximately half this class had reported that they had used alcohol in 1992 with increasingly higher probabilities at the subsequent three time-points. Class two is an increasing ever-used alcohol class. The CRPS increase consistently across time, although a small number of individuals said *yes* in 1992 (CRP = .14) that said *yes* in 1994 (CRP = .28). Class three is a low-use class, although a modest increase in a *yes* response is noted in 1998.

4.0 DISCUSSION

This study is the first to examine longitudinal panel data to identify typologies of adolescent self-reporters of lifetime cigarette, alcohol and marijuana use. The findings indicate that the adolescents participating in the NLSY study are generally consistent self-reporters. There was no clear class of users for any substance that wavered consistently in their self-reports of use. For example, no class of users for any substance had a pattern of reporting use, denying it at the next wave, endorsing in the next wave, etc.

We found that there were three classes for each substance that best fit the data. For the adolescents reporting cigarette use, the three classes indicate types of users. Class one was indicative of the early onset group. About half of them reported use at the first wave and two years later all reported use. Some recanting was revealed, in that the last two waves of data collection showed that 8% and 17% reported no use. Class two was representative of the late onset group with slightly more than half reporting use by the third wave and all reporting use by the final wave. The last group, class three, would represent those who were essentially non-users, in that a low percent reported use during the first three waves but then recanted use by the final wave.

Alcohol use also resulted in a three-class solution. Class one represents adolescents who are early onset users and who continue to be consistent reporters of their use. By the second wave, nearly all reported their use and did not recant. The second class represents users whose onset fell in the middle of the study period with about 30% using by the second wave, and 70% by wave three. The final group is the late onset group. They were nearly at zero for the first three waves of data collection and increased to just under 30% by the final wave. In sum, for alcohol use, there was no clear class of users who were consistent recanters.

The patterns for the three classes for marijuana are somewhat different compared to the other two substance use categories. Like the other two, there was a group that was late-onset and low-use without a clear pattern of recanting. The second class of marijuana users fell into a pattern of no-use for the first two waves but then all were users by 1996 and remained as such two years later. This group of marijuana users all reported their use for the last two waves with no indication of recanting. The final class were early-onset users. This last group reported almost no use at the first wave but by the second wave of data collection, all reported use. What is unique about this particular group is that about 30% recanted their use two years later and recanting increased to 43% by the last wave of the study.

For all three substances studied, there are similar types; the exact patterns are somewhat unique for each substance. We found that for each substance there was a late-onset group that remained consistent in their self-reports. A more moderate-onset group whose use started half way through the study period was also found, and their use for all three substances increased with no consistent recanting. The early-onset group for alcohol use revealed no sign of recanting, while cigarette users had about a 10% recant rate. The most dramatic recanting pattern was found for the early-onset group for marijuana, with about one-third recanting their use.

4.1 Strengths and Limitations

There are several strengths of this study. The data resulted in a large and carefully constructed sample and panel design, with carefully collected data. As such, the present study was able to examine self-report recanting among a large sample of youth for the three most common drugs of abuse for adolescents.

Although having access to a large, longitudinal dataset such as this has its advantages, the study is one based on secondary data analysis. The original study was not designed nor conducted with the purposes of the current project in mind. Another limitation is the lack of a larger number of waves of data. The typologies for each substance were identified using four waves of available data. The findings may reveal more complex patterns if we had more power and/or a longer time period over which to follow the participants through subsequent developmental periods. Hence, there is the possibility that the late- or moderate-onset groups that appear to be stable self-reporters may have exhibited some recanting if they were followed for several more waves.

The NLSY study instituted computerized interviews beginning in 2000 that were preprogrammed with the participant’s prior reported behaviors. Thus, if an adolescent reported their substance use at that wave of data collection, they would no longer be queried about their lifetime use again. There were a few earlier waves of data collection than what was analyzed here, but the number of users was so low for each substance that the current analyses would have been impractical.

It is not possible with the current data to identify motivations for the recanting revealed here. Future research is needed to follow adolescents from a young age through young adulthood and query substance use with biomarkers for validation. Only when later waves of data collection begin to reveal similar patterns of recanting could the investigators query participants for this issue.

Another limitation is the lack of control for misreporting. Thus, within these findings there may be subsets of youth who report use when in fact they had no lifetime use. Thus, the accurate self-report is actually in a latter wave of data collection when a denial of lifetime use is reported. Without biomeasures, it is not possible to confirm self-reported use or nonuse.

4. 2 Implications

For alcohol and cigarette use, it would appear that the late- and moderate-onset users report their lifetime use consistently with no clear recanting group surfacing. For alcohol users, even the early-onset group continued to be fairly consistent in their self-reports of use even four years later. For both cigarette users and marijuana users, we found that the early-onset users had a much higher propensity for recanting with about one-quarter to one-third doing so two and four years after reporting the use of these substances.

The results of these analyses suggest that youth who begin their use at an earlier age may not be as reliable reporters as youth who initiate use at later ages. It is possible that adolescents who begin use at an early age may be experiencing cognitive dissonance (Festinger, 1957) about their use as they get older, or there may be a link with their brain development such that early use is less reliably remembered. Moreover, it may be that youth who initiate use at an early age view such behavior at a later age as deviant, stigmatizing or socially undesirable, resulting in recanting at future survey waves as a way of being perceived as socially desirable (Sloan et al., 2004). More study is needed to identify underlying explanations for the unique subgroup of marijuana users who had such a high recant rate only a couple of years. Thus, future research is needed to explore these possibilities.

These findings also have important implications for the epidemiology and prevention of substance abuse in samples of adolescents and young adults. Our results suggest the veracity of prevalence estimates for licit and illicit substances could be different depending on the age of the respondent. Thus, reductions in self-reported substance use prevalence could be attributed to “successes” in public health interventions or policy, when in fact some these reductions are simply the result of misreporting or recanting over time. Ultimately, if the epidemiology of substance use or abuse is incorrect, we could be erroneously claiming victory when we should be stepping up efforts to reduce drug use in the young adult population.

Although computer assisted interviewing with automatically filled fields based on past responses will likely mitigate problems with report stability in future and current large-scale self-report surveys, some consideration of biological validation might be warranted. Specifically, when younger respondents report substance use, a certain proportion might be sampled for biological validation. In sum, the quality of reliable and valid reports of substance use can be enhanced with technology, but the issue is still of great concern to researchers and prevention professionals alike.

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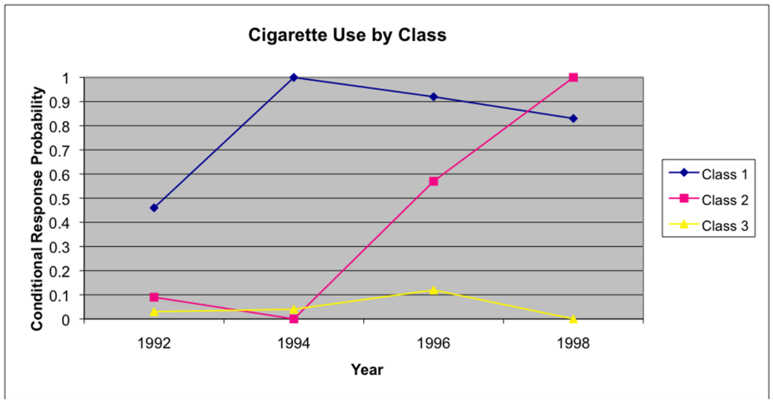

Figure 1.
Conditional response probability for cigarette use by class across four waves.

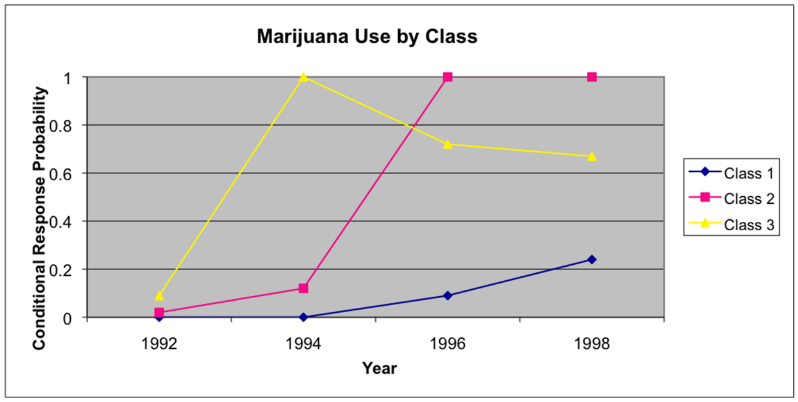

Figure 2.
Conditional response probability for marijuana use by class across four waves.

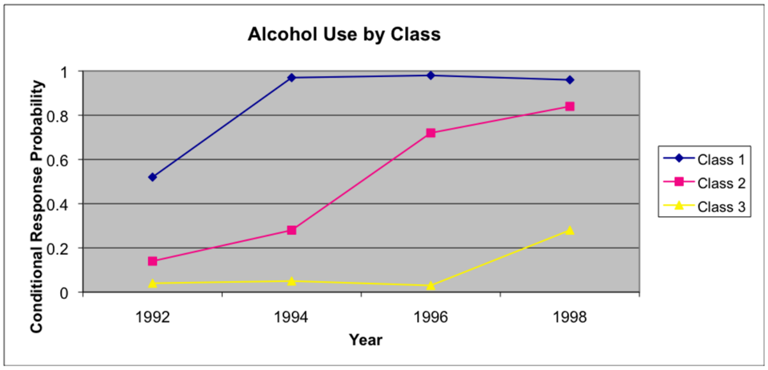

Figure 3.
Conditional response probability for alcohol use by class across four waves.

Table 1

Statistical indicators of overall model fit for the ever use cigarette variables

Number of	AIC	sBIC	LMRT	Entropy
2 Classes	3631	3645	$p<.001$	.769
3 Classes	3564	3587	$p<.001$	.975
4 Classes	3571	3602	$p>.05$	.827

AIC = Akaike Information Criterion

sBIC = sample size-adjusted Bayesian Information criterion

LMRT = Lo-Mendell-Rubin Test

Table 2

Conditional response probabilities for 3-class ever use cigarette solution

Ever Use Year	Class1	Class 2	Class 3
1992	.46	.09	.03
1994	1.00	.00	.04
1996	.92	.57	.12
1998	.83	1.00	.00

Note. The CRPs represent the probability that an individual within a class said *yes* to the *ever use* variable.

Table 3

Statistical indicators of overall model fit for the ever use marijuana variables

Number of Classes	AIC	sBIC	LMRT	Entropy
2 Classes	2573	2587	$p<.001$	.738
3 Classes	2572	2594	$p<.001$	.918
4 Classes	2580	2610	$p>.05$	.931*

AIC = Akaike Information Criterion

sBIC = sample size-adjusted Bayesian Information criterion

LMRT = Lo-Mendell-Rubin Test

*The loglikelihood value for this 4-class solution could not be replicated; do to the instability of this class solution, this model cannot be interpreted.

Table 4

Conditional response probabilities for 3-class ever use marijuana solution

Ever Use Year	Class1	Class 2	Class 3
1992	.00	.02	.09
1994	.00	.12	1.00
1996	.09	1.00	.72
1998	.24	1.00	.67

Note. The CRPs represent the probability that an individual within a class said *yes* to the *ever use* variable.

Table 5

Statistical indicators of overall model fit for the ever use alcohol variables

Number of Classes	AIC	sBIC	LMRT	Entropy
2 Classes	3633	3657	$p<.001$	.721
3 Classes	3610	3632	$p<.001$	.628
4 Classes	3617	3647	$p>.05$	.586

AIC = Akaike Information Criterion

sBIC = sample size-adjusted Bayesian Information criterion

LMRT = Lo-Mendell-Rubin Test

Table 6

Conditional response probabilities for 3-class ever use alcohol solution

Ever Use Year	Class1	Class 2	Class 3
1992	.52	.14	.04
1994	.97	.28	.05
1996	.98	.72	.03
1998	.96	.85	.28

Note. The CRPs represent the probability that an individual within a class said *yes* to the *ever use* variable.