The American Journal of Drug and Alcohol Abuse, 32: 41–53, 2006

ISSN: 0095-2990 print/1097-9891 online
DOI: 10.1080/00952990500328539

Risk for Marijuana-Related Problems among College Students: An Application of Zero-Inflated Negative Binomial Regression

Jeffrey S. Simons, Ph.D.,[1] Dan J. Neal, Ph.D.,[2] and Raluca M. Gaher, M.S.[1]
[1]University of South Dakota, Vermillion, South Dakota, USA
[2]University of Texas at Austin, Austin, Texas, USA

Abstract: *Method*: This study examined the association between marijuana-related problems and social norms, impulsivity, and perceived use utility among 292 college students. Zero-inflated negative binomial regression was used to simultaneously predict expected nonusers as well as predict counts of reported marijuana-related problems among expected users. Gender, social norms, impulsivity, and perceived use utility were used to predict expected nonusers as well as number of marijuana-related problems among expected users. *Results*: Only social norms were associated with the prediction of zero-values. In contrast, only perceived use utility was associated with the prediction of number of marijuana-related problems. *Conclusions*: Results generally are consistent with theories of the differential association of social-environmental and biopsychological variables with use and problems, respectively. Zero-inflated regression models are a useful strategy to examine risk behaviors with low base rates.

Keywords: Marijuana, impulsivity, social norms, expected utility, drug abuse, affect

Marijuana is the most commonly used illicit drug in the U.S. Approximately 46% of college students report having tried marijuana, 27% report use in the past year, and 16% report past 30-day use (1); thus, a significant

This research was supported in part by a National Institute on Drug Abuse grant DA15066 to Jeffrey S. Simons.
Address correspondence to Jeffrey S. Simons, 414 East Clark St., Department of Psychology, University of South Dakota, Vermillion, SD 57069. E-mail: jsimons@usd.edu

proportion of college students use marijuana. Furthermore, problems associated with use are, unfortunately, not uncommon. For example, short-term cognitive impairments and impairment in educational performance have been associated with heavy marijuana use (2–4). Given this, identification of individuals who use marijuana and report associated problems is an important issue. However, despite the relative prevalence of use, many college students have never tried marijuana or do not currently use it. As a result, an assessment of marijuana-related problems will yield a mixed distribution with a high number of zero-values. Some respondents will report not experiencing problems because they in fact did not use marijuana at all during the assessment window and those who do use the drug will report a range of problems including, for some users, zero. Identifying variables that predict nonusers as well as identifying predictors of the number of problems experienced among users are both of interest. Zero-inflated Poisson (ZIP; e.g., Lambert (5)) and a subsequent generalization of ZIP, Zero-inflated negative binomial regression (ZINB; e.g., Heilbron (6)) are two statistical techniques that allow one to accomplish both of these objectives in a single analysis. They, thus, represent parsimonious procedures that allow one to examine effects over the full distribution. These mixed distributions are a common feature in research investigating risk behaviors with low base rates (6).

Distributions of risk behaviors in general populations frequently will have a large number of zero-values. That is, a large proportion will not engage in the targeted risk behavior, while a smaller proportion of at risk individuals will report varying levels of the risk behavior and associated consequences. Such distributions pose difficulties for common statistical methods based upon normal distributions. ZINB regression models are one method for analyzing such data. ZINB models assume two distinct populations; one in which the target behavior is always absent, the other in which the target behavior can be any integer, including zero (6). More specifically, in the current study, one population would always score zero on a marijuana problems measure because they did not use marijuana during the assessed time period (current nonusers) and the other population could score any value, including zero, because they are engaging in the risk behavior (users—who may or may not experience problems). Thus, the prediction of counts is conditional upon the probability of the values being from a hypothetical subsample of participants that are predicted to “always” score zero on the measure. The model allows one to either use different sets of predictors to predict the two criterions (i.e., always zero-values and counts) or to utilize the same predictor set and evaluate whether variables are differentially associated with the respective criterions (7).

For the current study, we employed the same predictor set to predict zero-values (i.e., current nonusers) and counts (i.e., number of problems among expected users) in order to examine the differential predictive power of the variables of interest. Such differentiation is of theoretical interest in substance use research. That is, identifying both the types of variables that are associated with use initiation or low-level experimentation as well as the types of variables that are primarily associated with the prediction of use problems represents a common goal in substance use research. One model of substance use proposes that social-environmental variables are associated primarily with use initiation or low-level use while psychobiological variables are more strongly associated with use-related problems (8, 9). The role of psychosocial variables, such as use motives, expectancies, or perceived use utility do not clearly fit into this dichotomy. Indeed, these psychosocial variables have relations with both use and use-related problems (10–12). This study examined one social-environmental variable (social norms), one psychosocial variable (perceived marijuana use utility), and one biopsychological variable (impulsivity). Social norms are a social-environmental variable consistently associated with marijuana use (13, 14). Perceived use-utility is a psychosocial variable more associated with marijuana use than problems (12). In contrast, impulsivity is a biopsychological variable more associated with problematic use (15).

Social norms may be defined as either the actual or perceived behavior of individuals in social networks as well as the group member's attitudes toward target behaviors (i.e., whether group members think one should engage in the behavior). In the present study, social norms are represented by both the perceived marijuana use behavior and attitudes of peers. Social normative variables frequently are associated with marijuana use (13, 14, 16). Although the reason for this relationship traditionally has been attributed to the influence of social networks on use behavior, recent research on social norms and alcohol suggests that selection effects (i.e., choosing social networks with similar use practices) may also be of importance (17). Indeed, selection of marijuana using peer groups may be influenced by variables such as sensation seeking (13) and family relations (14). Such selection effects suggest that affective, cognitive, and social normative variables are not independent of each other. Individuals may be choosing social networks that not only have similar marijuana use practices but likely share common beliefs about the costs and benefits of marijuana. The potential interdependence of affective, cognitive, and social normative predictors of marijuana use makes their concurrent assessment of interest. In a study on drug refusal, peer influence is cited as a stronger influence on drug use decisions by low-level users while heavier drug users are more likely to cite emotional determinants and seldom cited peer influence as a factor (18). Thus, social norms may be more strongly associated with use initiation and low-level use rather than use-related problems.

Marijuana use, like many behaviors, may be influenced by the perceived costs and benefits of use. Evaluation of marijuana and other drug use has been operationalized in diverse ways, ranging from the global evaluation of attitudinal constructs (19) to specific expectancies of drug effects (20) to subjective expected utility models explicitly examining cost and benefits (21). An additional way of evaluating the perceived utility of drug use is to examine it in relation to personal goals (22). For instance, personal strivings are ongoing goals that individuals are characteristically trying to achieve through their behavior (23). Drug use is expected to increase to the extent that it is congruent with the attainment of such valued goals. Previous cross-sectional research has indicated that perceived conflict/utility of marijuana use in achieving personal strivings is associated with marijuana use initiation as well as frequency and problems (12). This study seeks to partially replicate this finding in a multivariate context.

Impulsivity is related to difficulty with the restraint of one's own behavioral and emotional responses (24). Impulsivity, although commonly referred to as "behavioral" undercontrol, also may be described as an over-reliance on affective rather than cognitive cues (25). Impulsivity has well-documented relations with substance use problems (8, 26, 27). Impulsivity has evidenced direct relations with marijuana-related problems above and beyond use frequency (15). Thus, impulsivity may likely be associated with use-related problems among expected users.

PURPOSE

The purpose of this study is to examine associations between social norms, impulsivity, perceived use utility and marijuana-related problems in a sample of undergraduates. Zero-inflated negative binomial regression is used to predict the current nonusers from the users in the sample, as well as the number of problems for the predicted users. Based on previous research, social norms are hypothesized to predict current nonusers, while impulsivity is expected to be associated with the number of problems experienced by the predicted users. Perceived use utility is hypothesized to be a significant predictor of both current nonusers as well as number of problems.

METHOD

Participants

Participants included 292 students at a small state university; all participated in research for partial fulfillment of course requirements. Women made up 70% of the sample. The sample ranged in age from 18 to 26 ($M = 19.69$, $SD = 1.56$); 94% were White, 1% Black, 2% Asian, 1% Native American, and 1% multiracial.

Measures

Marijuana Use and Problems

Lifetime marijuana use was assessed by a 7-point anchored rating scale (0 = no use, 6 = more than 300 days). Marijuana use in the last 30 days was assessed by a 9-point anchored rating scale (0 = no use, 8 = more than once a day).

Marijuana-related problems in the last 30 days were assessed by 23 items. Items were rated on a 5-point scale ranging from 0 (never) to 4 (more than 10 times). This scale was designed for adolescents and, thus, is appropriate for this population. This scale is internally consistent (alpha = .86) and has evidenced expected relations with marijuana use in previous research (11, 27). Sample items included "not able to do your homework or study for a test," and "felt physically or psychologically dependent on marijuana."

Impulsivity

Eysenck's Impulsivity Scale (29) includes 24 items assessing lack of control over behavior; each item is dichotomous. The alpha coefficients for men and women exceed .82 (29). Two items dealing specifically with drug use were excluded, yielding a 22-item scale. The alpha coefficient in this sample was .78. Sample items included "Do you often do and say things without stopping to think?" and "Are you an impulsive person?"

Social Norms

Social norms were assessed by the following three items:

1. Number of friends who use marijuana: 7-point anchored rating scale none (1) to all (7).
2. Friends' attitude toward participant using marijuana once a month or less: strongly disapprove (1) to strongly approve (5).
3. Friends' attitude toward participant using marijuana twice a month or more: strongly disapprove (1) to strongly approve (5).

The mean of the standardized items was used (alpha = .90).

Strivings Assessment

Personal strivings are "goals that lie directly behind individuals' behavioral choices (i.e., what an individual is characteristically trying to do)" (30). In the personal strivings assessment, participants first listed 10 personal strivings, with the instructions describing a personal striving as "an objective you are typically trying to accomplish." Participants were given examples such as "trying to be physically attractive," "trying to seek out new and exciting experiences," and "trying to avoid being noticed by others." Participants were instructed to think of actual instances of their behavior and to base their results on the actual intention of the behavior. Personal strivings were found to be stable in college students; 45% of the strivings listed at initial assessment were listed again 18 months later (31). The remainder of the assessment focused on the five strivings that the participants identified as most descriptive of themselves.

To assess perceived conflict/utility between strivings and marijuana use, the five strivings were entered into a matrix that included five columns to represent levels of marijuana use: (1) abstinence, (2) at least once a year but less than once a month, (3) at least once a month but less than once a week, (4) 1–3 days a week, and (5) most every day. The participant rated the extent to which each level of marijuana use would help or hinder the attainment of each personal striving using a 5-point scale (–2 = very harmful effect, +2 = very helpful effect) and a score was entered in each cell. A marijuana use–striving conflict/utility score was created for each personal striving (reverse scoring the abstinence column). Finally these sums were combined into a single marijuana use–strivings conflict/utility (i.e., use utility) score (alpha = .92). Higher scores correspond to greater perceived utility of marijuana in achieving goals. Lower (more negative) scores correspond to greater perceived conflict between marijuana use and goal attainment.

Procedure

Participants completed questionnaires online in small groups with adequate space to ensure privacy in a computer lab under the supervision of a research assistant. Previous research supports the reliability and validity of Internet-based assessment of drug use (32). All participants provided written informed consent. Participants generated a unique code for themselves and did not place their name on the questionnaires, thus, ensuring their anonymity. The assessment session lasted approximately one hour. Two previous manuscripts focusing on alcohol use have been derived from this dataset (33, 34).

RESULTS

Descriptive Statistics

Approximately 49% of the sample reported having used marijuana at least once in their lifetime and 21% reported use in the past 30 days. Average use in the last 30 days among those who had tried marijuana was 1–2 days (rating scale $M = 1.48$, $SD = 2.25$). The mean on the problems measure for those who had tried marijuana was 3.41 ($SD = 6.49$). Thus, a large percentage of participants reported no marijuana use and the mean number of problems was very low. ZINB models are designed for examining this type of distribution. Table 1 presents the summary statistics and correlation matrix for the predictors.

ZINB Model

The ZINB regression model was estimated with the ZINB command in Stata 8.0 (35) which solves for parameter estimates using maximum likelihood estimation. ZINB models have two sets of predictors, one set is used to predict zero-values (current nonusers in this case) and one is used to predict counts among the predicted users. All cases are used in both analyses but are weighted based on the results of the logistic component of the model (see below). In this manner, the model is predicting a zero-score to be generated from one of two populations. More specifically, one set of predictors is used in a logistic model, in which the likelihood of the observation being a current nonuser is computed, and a second set of predictors is used in a negative binomial model that predicts the count of expected problems, which may be zero or some positive integer. Thus, the probability that an observation is always zero is modeled by

Table 1. Summary statistics and correlation matrix of predictors

Variables	*M*(*SD*)	Range	1	2	3
Impulsivity	0.24 (0.20)	–0.18–0.77	.78		
Use utility	–0.85 (0.66)	–2.0–1.2	.14*	.92	
Social norms	2.11 (1.11)	1–5	.22**	.51**	.90

Note. $N = 292$, $^{*}p < .05$, $^{**}p < .001$, Cronbach's alphas are on the diagonal.

probability, ω, and the probability that the observation follows a negative binomial distribution with mean λ is (1-ω). More specifically,

$$\mathrm{P(Y = 0)} = \omega \tag{1}$$

$$\mathrm{P(Y \sim Negative\ Binomial}(\lambda, \alpha)) = (1 - \omega) \tag{2}$$

yielding the following distribution of counts:

$$\mathrm{P}(0) = \omega + (1 - \omega) * \mathrm{F}(0|\lambda) \tag{3}$$

$$\mathrm{P(k)} = (1 - \omega) * \mathrm{F(k}|\lambda) \tag{4}$$

where F represents the reference distribution (negative binomial with fixed parameter α), ω represents the predicted probability of being always-zero, modeled by the logistic component of the model, and λ represents the predicted mean of the negative binomial component of the model. While the data modeled in this study are not true count data, this analytic technique is appropriate for two reasons: first, the data are distributed exclusively on the nonnegative integers and tend to show heteroskedasticity (exactly like true count data); second, the data appear to be a true mixture model (thus, the need for zero-inflation). As such, even though the data technically are not generated by a count process, the resultant distribution has the important characteristics expected of a count process and, thus, a count model is appropriate.

Gender, social norms, use utility, and impulsivity were included as predictors in both components of the model (i.e., prediction of zero-values as well as the number of problems among the predicted users). Thus, the two-part model was parameterized as

$$\omega_i = \left(\mathrm{e}^{\beta^0 + \beta^1 * \mathrm{gender} + \beta^2 * \mathrm{norms} + \beta^3 * \mathrm{utility} + \beta^4 * \mathrm{impulsivity}}\right) \Big/ \left(1 + \mathrm{e}^{\beta^0 + \beta^1 * \mathrm{gender} + \beta^2 * \mathrm{norms} + \beta^3 * \mathrm{utility} + \beta^4 * \mathrm{impulsivity}}\right) \tag{5}$$

$$\lambda_i = \mathrm{e}^{(\beta^5 + \beta^6 * \mathrm{gender} + \beta^7 * \mathrm{norms} + \beta^8 * \mathrm{utility} + \beta^9 * \mathrm{impulsivity})} \tag{6}$$

The likelihood ratio for the full ZINB model was $\chi^2(9) = 109.47$, $p < .001$; maximum likelihood $R^2 = .31$, indicating that the overall model was significant. The maximum-likelihood R^2 is a measure of fit that is analogous to the coefficient of determination (R^2) in ordinary least squares (OLS) regression (e.g., Hardin and Hilbe, (36)). Both the logistic component of the model (LR $\chi^2(4) = 41.21$, $p < .0001$) and the negative binomial component of the model (LR $\chi^2(4) = 22.25$, $p = .0002$) were significant, indicating that the prediction of current nonusers and the prediction of marijuana-related problems were both significant.

Table 2. Zero-inflated negative binomial regression model

Variables	*b*	*S.E.*	*z*	*p* value
Problems				
Gender	–0.13	0.27	–0.49	.622
Social norms	0.14	0.13	1.09	.274
Impulsivity	1.16	0.62	1.86	.063
Use utility	0.70	0.20	3.47	.001
Nonusers				
Gender	–0.25	0.41	–0.62	.534
Social norms	–1.01	0.22	–4.68	<.001
Impulsivity	–1.77	0.97	–1.82	.068
Use utility	–0.60	0.33	–1.84	.066

Note. $N = 292$; $\chi^2(9) = 109.47$, $p < .001$, Maximum likelihood $R^2 = .31$.

Furthermore, support for the ZINB model over other possible count-data models was strong. The Vuong test for nonnested models supported the use of a zero-inflated model over a standard negative binomial model, $z = 3.51$, one-sided $p = .0002$, and the LR test for overdispersion also was significant (LR $\chi^2(1) = 152.96$, $p < .0001$) demonstrating that a ZIP model would be inappropriate.

With regards to the hypothesized predictors in the ZINB regression model, only social norms predicted zero-scores (i.e., expected current nonusers). Perceived use utility, impulsivity, and gender were not significant predictors of zero-scores. In contrast, perceived use utility was significantly positively associated with number of problems among expected users. Social norms, impulsivity, and gender were not significant predictors of number of problems among expected users. Full results of the regression analysis are presented in Table 2.

DISCUSSION

The results demonstrate that social norms and perceived use utility are related to nonuse and marijuana-related problems, respectively, among college students. The primary strength of this study is the use of ZINB regression to simultaneously predict current nonusers as well as the predicted count of marijuana-related problems among expected users. Differential results emerged in terms of statistical predictors of nonuse versus predicted marijuana-related problems; in particular, social norms differentiated expected nonusers from users, while perceived marijuana use utility predicted the number of problems in users. These results generally are consistent with models that propose social-environmental variables as being more associated with use initiation and low-level use and biopsychological variables as being more associated with use-related problems. However, it is important to note that such a result would not have been observable within the framework of the more traditional OLS regression analysis. Thus, the statistical modeling employed in this study allowed for the emergence of theoretically consistent results.

Examining each set of predictors more closely, both social norms and perceived use utility were hypothesized to predict current nonusers. However, only social norms and not perceived use utility was a significant predictor of current nonusers. In previous research, use utility has been significantly associated with use initiation (12). In the current study, use utility and social norms were fairly highly correlated, which may have contributed to the observed difference in the results. Much like traditional OLS regression, ZINB regression is susceptible to problems with multicollinearity, and these findings may be due to such a result.

As hypothesized, perceived use utility was associated with number of marijuana-related problems among expected users. Previous cross-sectional research has observed significant association between perceived use utility and marijuana-related problems (12). The current study provides a partial replication of this relationship in a multivariate context.

Impulsivity was hypothesized to be significantly associated with problems among expected users and to not be a significant predictor of current nonusers. However, impulsivity was associated marginally with both the number of problems among expected users and the prediction of current nonusers (p's $< .07$). Thus, the pattern of relationships did not conform to the hypothesis.

Several limitations should be noted. Marijuana use was quite low in the sample. Although the rates were equal to that reported in national samples, the extent to which these relationships hold among samples with higher rates of use and problems will need to be determined in future studies. Also, the sample was predominantly women and White, and generalization of the results to populations with different demographic characteristics needs to be determined. Finally, the cross-sectional analysis precludes causal interpretations. For example, longitudinal studies are needed to understand the relation between social norms and marijuana use behavior over time and, thus, examine the relative strength of social influence versus social selection effects.

The current study employed ZINB regression to predict marijuana-related problems in a mixed distribution of current users and nonusers in a sample of college students. The analysis approach provides a parsimonious way to analyze risk behaviors with low base rates. Furthermore, the analyses allowed for a theoretical separation of prediction of users versus nonusers, and predicted marijuana-related problems among predicted users. Results indicated that social norms predicted nonusers, while perceived use utility predicted the number of problems reported by expected users. Results generally were consistent with theories of the differential association of social-environmental variables and biopsychological variables with use and problems, respectively.

REFERENCES

1. Gledhill-Hoyt J, Lee H, Strote J, Wechsler H. Increased use of marijuana and other illicit drugs at US colleges in the 1990s: results of three national surveys. Addiction 2000; 95:1655–1667.
2. Block RI, Farnham S, Braverman K, Noyes R, Jr, Ghoneim MM. Long-term marijuana use and subsequent effects on learning and cognitive functions related to school achievement: preliminary study. In Residual Effects of Abused Drugs on Behavior. Spencer JW, Boren JJ, eds. Washington, DC: US Government Printing Office, 1990; 96–111.
3. Hall W, Johnston L, Donnelly N. Epidemiology of cannabis use and its consequences. In The Health Effects of Cannabis. Kalant H, Corrigall W, Hall W, Smart R, eds. Toronto: Addiction Research Foundation, 1999; 69–125.
4. Pope HG, Yurgelun-Todd D. The residual cognitive effects of heavy marijuana use in college students. JAMA 1996; 275:521–527.
5. Lambert D. Zero-inflated poisson regression, with an application to defects in manufacturing. Technometrics 1992; 34(1):1–14.
6. Heilbron DC. Zero-altered and other regression models for count data with added zeros. Biometric Journal 1994; 36:531–547.
7. Long JS, Freese J. Predicted probabilities for count models. The Stata Journal 2001; 1(1):51–57.
8. Glantz MD, Weinberg NZ, Miner LL, Colliver JD. The etiology of drug abuse: mapping the paths. In Drug Abuse: Origins & Interventions. Glantz MD, Hartel CR, eds. Washington, DC: American Psychological Association, 1999; 3–45.
9. Newcomb MD, Bentler PM. Substance use and abuse among children and teenagers. Am Psychol 1989; 44(2):242–248.
10. Christiansen BA, Smith GT, Roehling PV, Goldman MS. Using alcohol expectancies to predict adolescent drinking behavior after on year. J Consult Clin Psychol 1989; 57(1):93–99.
11. Simons J, Correia CJ, Carey KB, Borsari BE. Validating a five-factor marijuana motives measure: relations with use, problems, and alcohol motives. J Counsel Psychol 1998; 45(3):265–273.
12. Simons JS, Carey KB. Personal strivings and marijuana use initiation, frequency, and problems. Addict Behav 2003; 28:1311–1322.
13. Donohew L, Clayton RR, Skinner WF, Colon S. Peer networks and sensation seeking: some implications for primary socialization theory. Subst Use Misuse 1999; 34(7):1013–1023.

14. Hoffmann JP. The effects of family structure and family relations on adolescent marijuana use. Int J Addict 1995; 30(10):1207–1241.
15. Simons JS, Carey KB. Risk and vulnerability for marijuana use problems: the role of affect dysregulation. Psychol Addict Beh 2002; 16(1):72–75.
16. Maxwell KA. Friends: the role of peer influence across adolescent risk behaviors. J Youth Adolesc 2002; 31(4):267–277.
17. Bullers, S, Cooper, ML, Russell, M. Social network drinking and adult alcohol involvement: A longitudinal exploration of the direction of influence. Addict Behav 2001; 26(2):181–199.
18. Jenkins JE. Rural adolescent perceptions of alcohol and other drug resistance. Child Study Journal 2001; 31(4):211–224.
19. Simons J, Carey KB. A structural analysis of attitudes toward alcohol and marijuana use. Pers Soc Psychol Bull 1998; 24(7):727–735.
20. Schafer J, Brown SA. Marijuana and cocaine effect expectancies and drug use patterns. J Consult Clin Psychol 1991; 59:558–565.
21. Bauman KE, Fisher LA, Bryan ES, Chenoweth RL. Relationship between subjective expected utility and behavior: a longitudinal study of adolescent drinking behavior. J Stud Alcohol 1985; 46(1):32–38.
22. Maggs JL. Alcohol use and binge drinking as goal-directed action during the transition to postsecondary education. In Health Risks and Developmental Transitions During Adolescence. Schulenberg J, Maggs JL, eds. New York: Cambridge University Press, 1997; 345–371.
23. Emmons RA. Personal strivings: an approach to personality and subjective well-being. J Pers Soc Psychol 1986; 51:1058–1068.
24. Plutchik R, Van Praag HM. The nature of impulsivity: definitions, ontology, genetics, and relations to aggression. In Impulsivity and Aggression. Hollander E, Stein DJ, eds. New York: John Wiley & Sons, 1995; 7–24.
25. Donohew L, Zimmerman R, Cupp PS, Novak S, Colon S, Abell R. Sensation seeking, impulsive decision making, and risky sex: implications for risk-taking and design of interventions. Pers Indiv Diff 2000; 28:1079–1091.
26. Brady KT, Myrick H, McElroy S. The relationship between substance use disorders, impulse control disorders, and pathological aggression. Am J Addict 1998; 7(3):221–230.
27. Vitaro F, Ferland F, Jacques C, Ladouceur R. Gambling, substance use, and impulsivity during adolescence. Psychol Addict Beh 1998; 12(3):185–194.
28. Johnson V, White HR. An investigation of factors related to intoxicated driving behaviors among youth. J Stud Alcohol 1989; 50:320–330.
29. Eyseneck SBJ, Eysenck HJ. Impulsiveness and venturesomeness: their position in a dimensional system of personality. Psychol Rep 1978; 43:1247–1255.
30. Emmons RA, King LA. Conflict among personal strivings: immediate and long-term implications for psychological and physical well-being. J Pers Soc Psychol 1988; 54:1040–1048.
31. Emmons RA. The personal striving approach to personality. In Goal Concepts in Personality and Social Psychology. Pervin LA, ed. Hillsdale, NJ: Erlbaum, 1989; 87–126.

32. Miller ET, Neal DJ, Roberts LJ, Baer JS, Cressler SO, Metrik J, Marlatt GA. Test-retest reliability of alcohol measures: is there a difference between Internet-based assessment and traditional methods? Psychol Addict Beh 2002; 16(1):56–63.
33. Simons JS. Differential prediction of alcohol use and problems: the role of biopsychological and social-environmental variables. Am J Drug Alcohol Abuse 2003; 29(4):861–879.
34. Simons JS, Christopher MS, McLaury AE. Personal strivings, binge drinking, and alcohol-related problems. Addict Behav 2004; 29:773–779.
35. StataCorp. Stata Statistical Software: Release 8.0. Stata Corporation: College Station, TX, 2003.
36. Hardin J, Hilbe J. Generalized Linear Models and Extensions. Stata Press: College Station, TX, 2001.