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Do child physical abuse and adolescent peer relationships influence typologies of illegal and substance-use behaviors during emerging adulthood?

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Do Child Physical Abuse and Adolescent Peer Relationships Influence Typologies of Illegal and Substance-Use Behaviors During Emerging Adulthood?

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This study uses latent class analysis (LCA) to explore patterns of illegal behaviors (e.g., property and violent offenses), and substance use (e.g., alcohol, tobacco, or other drugs) among emerging adults (18 to 27 years). Data include 12,677 respondents from Wave 3 of the National Longitudinal Study of Adolescent Health (Add Health). Our study found that behaviors clustered into the following four classes: (a) the illegal and substance-use behaviors class (5.33%); (b) the fighting and substance-use class (5.24%); (c) the substance use class (28.30%); and (d) the normative class (61.12%). The analysis also incorporates indicator variables from Wave 1 onto the latent classes using the 3-step approach. Emerging adults most likely to be in the illegal and substance-use behaviors class with the highest prevalence of illegal behaviors were male; Black; younger; had histories of childhood physical abuse; or had friends at Wave 1 who drank, smoked, or used marijuana. Similarly, those most likely to be in the fighting and substance use class were male, Black, younger, reported childhood physical abuse, and had friends during Wave 1 who smoked or drank alcohol. Members of the fighting and substance-use class were also less educated than members of other classes. The substance use class was younger, less educated, less likely to be Black, had been physically abused, and had friends during Wave 1 who smoked or drank. Within the substance use class, no significant differences were found based on sex. We also found significant direct effects between peer influences and latent class indicators. Overall, results highlight the enduring influence of physical abuse and adolescent peer relationships.

Key words: latent class analysis, illegal behavior, substance use, peers, emerging adults

Numerous studies of adolescent delinquency have linked involvement in illegal and substance-use behaviors with negative peer influences (c.f., Shaw & McKay, 1969; Short Jr., 1957) and childhood physical abuse (Curtis, 1963; Widom & Maxfield, 2006; Widom, Marmorstein, & Raskin White, 2006). However, few studies have explored the factors contributing to illegal behaviors among emerging adults (i.e., 18 to 25 years old). Specifically, no available studies have examined the ways in which physical abuse experienced during childhood and peer relationships experienced during adolescence might influence emerging adults' patterns of illegal and substance-use.

American society has undergone enormous demographic changes since the 1950s that have altered the expected life course for young adults. Many scholars now acknowledge that the process of becoming an adult generally extends beyond the age of 18 years, and recognize *emerging adulthood* as a distinct developmental stage. Because parental monitoring typically diminishes following adolescence, many emerging adults engage in problematic behaviors while seeking varied experiences before settling down as responsible adults with the constraints of careers and long-term relationships (Arnett, 2000, 2005, 2007; Arnett & Tanner, 2006).

As compared with other age groups, emerging adults experience disproportionate rates of substance use and incarceration. Specifically, emerging adults experience more problems associated with alcohol consumption, and this group has reported abusing a wider range of illicit drugs (e.g., marijuana, cocaine; Substance Abuse and Mental Health Services Administration, 2010). Although rates of substance use among emerging adults might explain some involvement with the criminal justice system, substance use alone does not explain the disproportionate number of emerging adults in prison. In 2008, emerging adults accounted for only 9.9% of the nation's population (U.S. Census Bureau, n.d.) but comprised 14.7% of the U.S. prison population (American Correctional Association, 2008).

To better understand the sequelae of problematic behaviors among emerging adults, this study's conceptual framework amalgamated key aspects of two theories: the cycle of violence theory and the theory of social learning. This conceptual framework is based on the premise that the family and peer relationships an individual establishes before entering emerging adulthood will continue to shape his or her behavior not only as an emerging adult but also well into the adult years (Akers, 2002). The study sample was drawn from Wave 3 of the National Longitudinal Study of Adolescent Health (Add Health), and covariates from Waves 1 and 3 were used to determine the ways in which early experiences influence illegal and substance-use behaviors during emerging adulthood.

Physical Abuse and the Cycle of Violence

Curtis (1963) asserted that physical abuse can function as a conduit to problematic behaviors, acting either through parental modeling of violence or as a result of the hostility children feel in response to the abuse they have experienced. Thus, the cycle of violence theory posits that being a victim of physical abuse elevates an individual's risk for both engaging in illegal behaviors (Widom, 1989; Widom & Maxfield, 2001) and substance use (Widom & Hiller-Sturmhofel, 2001; Widom et al., 2006). Studies applying this theoretical framework found an association between experiences of physical abuse and later criminal behaviors and substance use during adulthood (Widom & Maxfield, 2006; Currie & Tekin, 2006; Fagan, 2002).

Peers and Social Learning Theory

The cycle of violence aligns well with social learning theory, which is a general theory of problematic behaviors such as substance use and illegal behaviors. According to the social learning theory, modeling (i.e., demonstrating) and reinforcement facilitate the process of learning to either engage or abstain from illegal and substance-abuse behaviors. For example, when peers use substances, those peers both model and reinforce the acceptability of substance-use behaviors (Akers, 1999; Akers & Jennings, 2009; Bandura, 1973, 1977, 1978). In fact, youth who associate with peers who use tobacco, alcohol, or marijuana are more likely to engage in illegal behaviors and substance use (Centers for Disease Control and Prevention [CDC], 1994; Urberg, Luo, Pilgrim, & Degirmencioglu, 2003). Moreover, gang membership escalates the risk of engaging in illegal behaviors beyond the level of having friends who engage in illegal activities (Battin, Hill, Abbott, Catalano, & Hawkins, 1998; Gatti, Tremblay, Vitaro, & McDuff, 2005).

Within social learning theory, an individual's location in the social structure can be distinguished by age, gender, and race indicators. As such, these indicators influence the extent to which an individual engages in prosocial or antisocial behaviors through social learning variables, including differential association (e.g., associating with peers who use substances) and modeling (e.g., imitating the violence a parent demonstrates when physically abusing a child; Akers & Lee, 1999). Plots of crime rates by perpetrator age show a steep upward slope during adolescence, a peak of activity during emerging adulthood, followed by a downward slope in the adult years (Hirschi & Gottfredson, 1983). Several scholars have used the term *age-crime curve* to describe this shift in deviant behaviors over time (Agnew, 2003; Sampson & Laub, 2005). Schwartz and colleagues (2010) demonstrated the influence of gender on deviant behaviors, showing males were at greater risk of substance-use behaviors than females. Likewise, numerous studies have found that males were more likely than females to engage in illegal behaviors (Connell, Cook, Aklin, Vanderploeg, & Brex, 2011; Farrington et al., 2010; Schwartz et al., 2010). In addition, several studies have compared emerging adults by race/ethnicity and described a phenomenon referred to as the *cross-over effect*. Although such studies found Black emerging adults had lower rates of substance use than their White or Hispanic counterparts, by age 35 years the substance-use rate among Blacks "crosses over" to eclipse the rates of Whites and Hispanics (Arnett & Brody, 2009).

From the perspective of the social learning theory, educational attainment can signify an individual's commitment to "conventional lines of action," or a lower risk for problematic behaviors. Thus, individuals who earn a college degree could be considered as being more conventional than those who completed less formal education (e.g., dropouts; Akers, 2009). Nonetheless studying deviant behavior among college students remains important work. Those interested in this area should see Akers' (2009) exploration of problematic behaviors among college students. Other scholars have highlighted risky behaviors, such as binge drinking, that often accompany the college experience (White et al., 2006; Arnett, 1994).

Person-centered analyses. Until recently, most studies comprising the literature exploring illegal behaviors were hampered by certain limitations, including having focused on a singular type of behavior (e.g., violent, property, or substance-related offenses) or having created a scale that failed to capture the interrelationships of problematic behaviors. Given these limitations, the existing studies do not convey the complexity and variability of illegal behaviors. For example, the available studies have not adequately explored how substance use covaries with illegal behaviors, leaving a critical knowledge gap that has hindered the development of successful interventions for these co-occurring behaviors. Fortunately, a class of methodologies termed *person-centered analyses* enables scholars to discern patterns of characteristics shared by a subgroup and distinguishing one subgroup from others. Conversely, variable-based methods rely on least-square approaches to determine the extent to which dependent variables are explained by manipulating independent variables through correlations or regression (Collins & Lanza, 2010; Nurius & Macy, 2008). Both research and theory support the use of person-centered techniques to more fully understand the origins and trajectories of illegal behaviors (Wiesner & Windle, 2004; Snyder & Medeiros, 2013).

Rather than focusing on a single developmental period, most of the studies using person-centered analytic techniques have concentrated on the ways in which illegal behaviors evolve over time (Odgers et al., 2008; Spoth, Reyes, Redmond, & Shin, 1999). Studies that aim to explore typologies during a single time point use latent class analysis (LCA), which is a person-centered analytic technique that identifies the probabilities of behavioral patterns based on individuals' responses to observed measures (i.e., survey questions; Muthén, 2002). Studies that have used LCA to examine substance-use without illegal behaviors have found three to six classes of behavioral patterns (e.g., abstainers, experimenters, single substance users, polysubstance users; Cleveland, Collins, Lanza, Greenberg, & Feinberg, 2010; Lynskey et al., 2006; Shin, Hyokyoung, & Hazen, 2010). These studies have used multinomial logistic regression to regress covariates such as peer substance use and physical abuse onto the latent classes. Shin et al. (2010) found peer substance abuse was significantly related to class membership for both females and males, whereas low-to-moderate physical abuse was not related to class membership. Lynskey et al. (2006) found that physical abuse increased the likelihood of membership in the polysubstance use class.

LCA studies of illegal behaviors without substance use found three to nine classes of behavioral patterns (Brownfield & Sorenson, 1987; Francis, Soothill, & Fligelstone, 2004; Odgers et al., 2008). One study with a female-only sample and one study with a male-only sample found three classes of delinquent behavior, ranging from normative (nonoffending) to the most severe delinquent behaviors. In both studies, the most severe class had the smallest number of members (Brownfield & Sorenson, 1987; Odgers et al., 2008).

To date, only a recent study conducted by Connell et al. (2011) has used LCA to explore peer influence on patterns of illegal behaviors and substance use. Connell and colleagues conducted LCA on data obtained from a sample of 1,820 students enrolled in Grades 8 through 10 (54% female) in Connecticut to determine how peers influenced patterns of eight illegal behaviors (e.g., violent offenses, property offenses, drug sales, drug purchases) and their consequences (e.g., arrests, suspension, police involvement). The study, which did not disaggregate the sample by gender, identified four classes of illegal behaviors (the authors used the term antisocial behaviors [ASB]): nonoffending (i.e., normative, 37%), mild (45%), moderate (12%), and severe (6%) illegal behaviors. The most frequently reported behavior was picking a fight with someone who was not family (24.4%) and the least frequently reported behavior was selling drugs (3.1%).

Connell et al. (2011) measured peer-level risk by averaging the number of the participants' close friends who used alcohol, tobacco, and other drugs. Because the peer-level risks were averaged, it was not possible to discern whether tobacco, alcohol, or another drug had a greater association with illegal behaviors. Similarly, because substance use was measured with a single item, it was not possible to explore how patterns of substance use covaried with other illegal behaviors. Another limitation of the Connell et al. study was that race/ethnicity was not included as a covariate in the analysis because Caucasian youth constituted 83% of the sample. This nonrepresentative sample was especially problematic because both research and crime statistics indicate Black youth have an elevated risk of illegal behaviors (Franke, 2000; Martin et al., 2011).

Despite those limitations, Connell and colleagues' (2011) findings made a meaningful contribution to the literature because their study showed youth in the serious illegal behavior class (their label was *antisocial behavior*) were nearly 3 times (OR 2.91, $p < 0.01$) more likely to be male. In addition, the Connell et al. study findings demonstrated that exposure to substance-using peers was a consistent, negative influence that led to youth's increased involvement in illegal offenses. In particular, youth who reported peers' substance use were 8.46 times more likely ($p < 0.01$) to be in the serious illegal behavior class than the normative group.

Study Purpose

The purpose of the study was to address the gaps in the extant literature and to explore patterns of illegal behaviors and substance use with a national sample of emerging adults. To this end, the study asked the following research questions: Do patterns of illegal behaviors and substance use result in distinct subpopulations of emerging adults? Is child physical abuse (retrospectively asked during Wave 3) correlated with different latent classes during emerging adulthood (Wave 3)? Are peer influences during adolescence (Wave 1) correlated with different latent classes during emerging adulthood (Wave 3)? Do these patterns differ based on age, gender, and race? To answer these questions, the study proposed the following four hypotheses:

- **Hypothesis 1.** We hypothesize that, using variables for violent offenses, property offenses, and substance use behaviors, a latent class analysis will identify distinct subpopulations among emerging adults.
- **Hypothesis 2**. We hypothesize that a history of physical abuse would elevate the risk for class membership in the most severe illegal and substance-use behavior class.
- **Hypothesis 3**. We hypothesize that peer influences during adolescence would elevate the risk for class membership in the most severe illegal and substance-use behavior class.
- **Hypothesis 4.** We hypothesize that emerging adults who are younger, male, and Black will be at greater risk of being in the class with the most severe illegal and substance-use behaviors.

Method

Data Source

This study used data from Waves 1 and 3 of Add Health. Congress mandated the Add Health study to examine adolescent health and risk behaviors (Carolina Population Center, n.d.). In 1994, the Wave 1 Add Health in-school survey was completed by 90,118 youth. Drawing from this pool of respondents, a subsample was randomly selected for the Wave 1 in-home interviews. The in-home sample, which was stratified by grade and gender, consisted of 20,745 youth in Grades 7 through 12 (ages 11 to 21 years). The Wave 2 data were collected between April and August 1996, using an in-home interview with 14,738 youth (ages 12 to 21years) who had participated in the Wave 1 interviews. Wave 3 included data from 15,197 emerging adults (ages 18 to 28 years) collected between August 2001 and April 2002 (Harris et al., 2009).

Complex design. Both the schools and the students chosen to participate in Add Health were selected with unequal probabilities. To ensure that analyses estimates were not biased, the present study's analysis included only respondents with sampling weights, strata, and cluster variables (Chantala, 2006).

Table 1
Demographic Characteristics of Unweighted Respondents

	Male %		**Female %**		**Total Sample (*N*= *12,677*)**	
	M/n	**(*SD*)**	***M/n***	**(*SD*)**		**(*SD*)**
Age (at Wave 3)	22.12	(1.75)	21.88	(1.75)	21.99	(1.75)
Gender	5,847		6,830		12,677	
Hispanic						
Yes	16.66		15.12		15.83	
Race						
American Indian	1.08		1.22		1.15	
Asian/ Pacific Islander	7.54		6.41		6.93	
Black	17.65		21.57		19.22	
White	61.04		59.65		60.29	
Biracial	4.28		4.49		4.39	
Multiracial	0.41		0.48		0.45	
Other	8.00		7.17		7.56	
Education (at Wave 3)						
< High school	9.70		7.45		8.49	
High school/equivalent	73.66		70.44		71.93	
Some college	6.64		7.80		7. 27	
College	9.41		13.44		11.58	
Beyond college	0.60		0.86		0.74	

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Study Sample

The study sample included 12, 677 respondents who participated in Waves 1, 2, and 3 of Add Health data collection. Table 1 provides the demographic characteristics of the sample.

Measures

Illegal behaviors. This study included a range of dichotomous behaviors drawn from Wave 3 under the rubrics of property offenses, violent offenses, and substance use. Items were re-scaled so that 0 equaled *never* and 1 equaled *one or more times*.

Property offenses. Respondents were asked whether they had committed any of the following five property offenses during the past 12 months: (a) deliberately damaged property; (b) stole something worth more than $50; (c) entered "a house or building to steal something;" (d) "stole something worth less than $50"; and (e) bought, sold, or held stolen property.

Violent offenses. Respondents were asked four questions to assess the extent of their engagement in violent behaviors over the past 12 months: (a) someone needed medical treatment by a doctor or nurse after a fight; (b) pulled a knife or gun on someone; (c) used or threaten to use a weapon; (d) used a weapon in a fight.

Substance use. To assess respondents' experience with tobacco, alcohol, or other drugs, respondents were asked questions that captured whether they had (a) smoked cigarette during the past 30 days; (b) had alcohol-related problems with friends during the past 12 months, (c) used marijuana since Wave 1, or (d) used cocaine since Wave 1. A final substance-related question pertaining to drug sales asked respondents if they had sold marijuana or other drugs during the past 12 months.

Demographics. The Wave 1 interviews collected baseline demographic information based on respondents' self-reports of sex, race/ethnicity, and age. For the present data analysis, sex (*male* = 1), Hispanic (*Hispanic* = 1), and race (*Black* = 1) were dummy coded. The respondents' dates of birth reported at Wave 1 were used to calculate their ages at Wave 3. Ages were standardized (M = 0, SD = 1). During Wave 3, respondents were asked to report the highest level of education they completed by choosing 1 of 5 response options: (a) did not complete high school, (b) completed high school or GRE [Graduate Record Exam], (c) completed some college or an associate's degree, (d) completed college, (e) completed advanced degree (e.g., master's degree, PhD, or medical doctor). Education was standardized (M = 0, SD = 1).

Child physical abuse. During Wave 3 interviews, respondents were asked to recall the number of times their "parents or other adult caregivers slapped, hit, or kicked you?" by the time they were in the sixth grade. Based on the work of Currie and Tekin (2006), the present study used a dichotomous measure of physical abuse when the respondent reported 10 or more occurrences.

Peer influences. Four items explored peer influences. Three separate items in the Wave 1 interview captured the extent to which the youth's three best friends used substances: "How many [close friends] drink alcohol at least once a month?"; "How many smoke at least 1 cigarette a day?"; and "How many use marijuana at least once a month?" The last item assessing peer influences was asked during the Wave 3 interviews, and inquired whether the respondent had "belonged to a named gang." This item was dummy coded (*belonging to a gang* = 1).

Statistical Analysis

The first step in the preparing the data for analysis was to examine the correlations of all variables that would be used in the LCA in Stata 12.1 to ensure none of the variables were highly correlated. The data were then transferred to Mplus version 7 (Muthén & Muthén, 2010) using the stata2mplus program (Institute for Digital Research and Education, 2013). The Mplus syntax is provided in the Appendix.

LCA assumptions. Before discussing the analysis in Mplus, an explanation of LCA's two key assumptions may be helpful. First, the conditional response probabilities for each individual in a latent class are assumed to be the same. Second, the assumption of *conditional independence* (also termed *local independence*) asserts that within each class the indicators (i.e., individual items or survey questions) are independent of one another. Conditional independence enables us to express the probability of a particular pattern of responses conditioning on latent class only (Collins & Lanza, 2010; Lanza, Flaherty, & Collins, 2003). Although numerous critiques of conditional independence exist, the following section summarizes just a few. Unfortunately, "sometimes the constraints imposed by conditional independence are unrealistic" (Hagenaars, 1988, p. 380). In this vein, Uebersax (1999) asserted that relaxing conditional independence enabled LCA to better model typologies that occur in nature. Similarly, Reboussin, Ip, and Wolfson (2008) contended that researchers should expect to violate the local independence assumption when examining typologies of behaviors such as drinking because each behavior would likely be related to others (e.g., binge drinking and having a hangover). To relax the assumption of conditional independence, this study's analysis allowed items to be correlated (Muthén, 2004; Muthén, & Muthén, 2012; Nylund, n.d.).

Estimation. Mplus uses the expectation maximization (EM) and the Fisher scoring (FS) algorithms (Muthén, & Muthén, 2012). The EM algorithm alternates between expectation and maximization steps to estimate LCA models' parameters. During each step, current estimates are compared to the estimates obtained in the previous step. The program converges on a maximum likelihood function when differences between estimates become smaller than a specified criterion. Although identifying a single model would be ideal, this process might yield numerous solutions that correspond to different local maxima (Lanza et al., 2003; Snyder & Medeiros, 2013). Because few emerging adults reported stealing something worth over $50 this variable approached zero. FS accounts for extreme cases close to zero or 100% responses. FS applies a modified version of the Newton-Raphson iterative method. Within FS, expected values replace the second derivatives of log-likelihood function (Bock, 1997).

Parameter estimation. Because the study included categorical outcomes and a minimal amount of missing data on the dependent variables, the computations required numerical integration. Thus, the analyses used the Monte Carlo simulation technique as the parameter estimation method (Muthén & Muthén, 2012). The Monte Carlo simulation techniques enables the analyst to produce sample Bayesian analysis data with known parameter estimates, and to evaluate how such indices perform under differing conditions. Thus, we analyze the data with different models than what the data in our sample holds and we are able to evaluate how the fit indices and tests perform. To be certain that the summary information that was calculated had a sufficient degree of reliability we generated 500 replications (Nylund, Asparouhov, Muthén, 2007).

LCA model fit. Prior to adding covariates to the model, separate LCA were conducted with the 15 illegal behavior and substance-use variables from Wave 3 (see Table 2). The modeling process began by fitting the 15 illegal behavior and substance-use variables with a one-class model, and classes were increased until the model no longer improved. According to McCutcheon (2002), although models with a greater number of parameters technically fit the data best, the ideal solution is the most parsimonious model that has an acceptable fit to the observed data. Thus, the objective of determining model fit is not for fit statistics to *bottom out* or have the lowest possible values. Instead, a model should be selected when the model is interpretable or substantively meaningful and parsimonious. Here the prior literature helps determine the best model. It is also useful to examine the item response probabilities from each model (Collins & Lanza, 2010).

With that logic in mind, latent class models are evaluated based on statistical outcomes, called *model fit statistics*, and evaluation of the usefulness of the model, called *model usefulness*. The model fit statistics include the log likelihood, the Bayesian Information Criteria (BIC), the Aikaike Information Criteria (AIC; Akaike, 1974), and the Lo-Mendell Rubin Test (LRT). After accounting for interpretability and parsimony, the lowest values are preferable with the log likelihood, BIC, and AIC. The LRT tests whether the current model is preferable to a model with one less class (i.e., K classes versus K-1 classes; Lo, Mendell, & Rubin, 2001). Entropy is one measure of model usefulness, and ideally, model entropy should be as close to one as possible. It is also useful to review the different latent classes and assess intuitively which class is the best fit (Nylund, Bellmore, Nishina, & Graham, 2007). The conditional independence assumption was checked by examining the bivariate standardized residual z-scores in excess of |1.96| using the tech10 output option in Mplus (Muthén, 2009).

Next, the model with the best fit was run a second time to test whether the class structure changed after relaxing conditional independence. Because this step is a computationally intensive process, the pairs of variables that violated conditional independence were added to the models one at a time. Then conditional independence was checked and the process was repeated. Because several items had minimal violations, only the most severe violations of conditional independence were relaxed by adding their residual covariances to the analysis (L. Muthén, 2013 personal communication, May 9, 2013; R. Medeiros, 2013 personal communication, May 1, 2013).

To validate these results, the sample was randomly divided in half in Stata 12.1. Then, the optimal model fit was determined using the first subsample, and then the process was repeated for the second half of the sample. When the model fit for both halves of the model matched the full sample model, we felt confident that we had correctly specified the model fit. To confirm that both halves were identical, the data were compared using plots of the AIC, BIC, and sample-size-adjusted BIC (SSA; Collins & Lanza, 2010).

Once the correct model had been established, the next step was to incorporate covariates (e.g., demographic and peer variables) into the four-class model using the 3-step approach developed by Vermunt

(2010). During the first step, latent classes are formed without adding covariates. In the second step, the latent class posterior distribution is used to create variable *S*, which represented the most likely class. During the third step, the measurement error for *S* was accounted for while the model was estimated with the auxiliary variables (Asparouhov & Muthén, 2012). All analyses accounted for data stratification, clustering, and sampling weights. Figure 1 provides a visual depiction of these analyses.

Missing data. To ensure accurate analysis, the study sample was limited to the 14,206 cases with weights and cluster variables (Chantala, 2006). Because Mplus uses listwise deletion for missing covariates that are regressed onto the classes, 1,529 cases were deleted from the sample due to missing covariates, reducing the analytic sample to 12,677 cases. With the exception of responses to substance abuse variables, such as being sick after drinking or having problems with friends due to alcohol, the patterns of missing data were missing at random. It is not uncommon for the missingness of substance-use items to be nonrandom

Attrition Analysis. Because the sample lost 1,529 cases following the listwise deletion of cases that were missing covariates, an attrition analysis was conducted to compare the attrited participants to those included in the final analytic sample. The results showed respondents in the analytic sample were slightly older and more educated than the attrited cases. In addition, the attrited cases included a higher proportion of Black and Hispanic respondents. Although no differences were found for property offenses between attrited cases and the analytic sample, the comparison showed differences existed between the two groups on the variables for the following illegal behaviors and substance-use behaviors: As compared with attrited cases, study participants were less likely to cause severe physical injury during a fight (i.e., injury requiring medical attention; $p < .01$), more likely to use a weapon in a fight ($p < .05$), and more likely to use marijuana ($p < .01$).

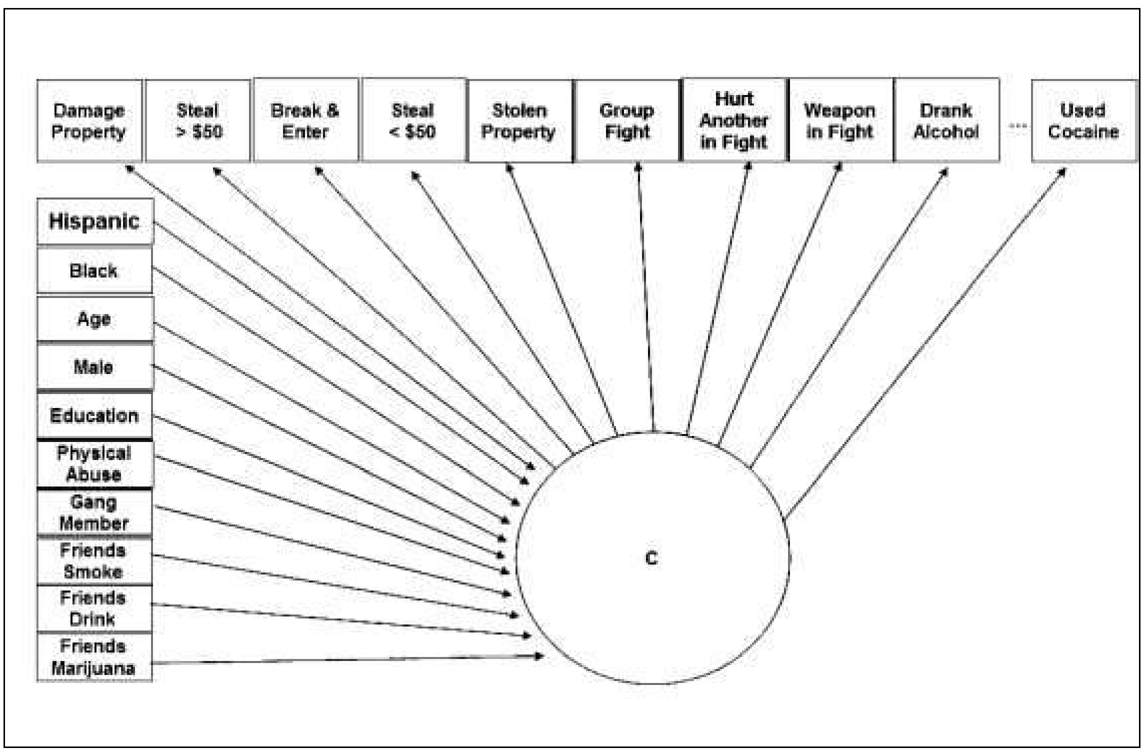

Figure 1. Latent class analysis diagram

Note: The boxes above the circle represent the illegal and substance-use behaviors reported at Wave 3; the ellipses between the last two boxes indicate that not all of the variables used in the LCA are included in this diagram. The circle with the C represents the classes that were formed based on the illegal and substance use variables. The boxes on the left represent the covariates that were regressed onto the classes.

Table 2

Unweighted Prevalence of Illegal and Substance-Use Behaviors (N =12, 677)

	Females %	Males %	Total %
Damage property	4.20	14.12	8.77
Steal > $50	1.92	4.84	3.26
Enter building to steal something	0.95	2.76	1.78
Steal < $50	4.81	10.83	7.58
Stolen property	1.86	7.71	4.56
Hurt someone fighting - required medical care	2.13	8.88	5.24
Group fight	3.09	14.30	8.27
Used/threaten weapon	0.98	3.08	1.95
Used weapon in fight	0.75	2.98	1.78
Sell drugs	3.54	11.61	7.25
Smoked cigarette during past 30 days	36.37	41.37	38.67
Alcohol related problems with friends	8.23	13.75	10.86
Sick/threw up after drinking	48.19	50.41	49.24
Used marijuana since Wave 1	39.25	51.22	44.77
Used cocaine since Wave 1	8.04	12.37	10.03

***Note*.** Illegal and substance-use behaviors were reported at Wave 3. Unless otherwise indicated the behaviors occurred within the past 12 months of. Wave 3 data collection

Results

Table 2 provides the prevalence of illegal and substance-use behaviors for the sample. In the study sample, using marijuana was the most common behavior for emerging adults of either gender (females = 50.93%, males = 39.11%). The least common behavior for females was using a weapon in a fight (females = 0.75%) whereas the least common behavior for males was entering a building to steal something (males = 2.76%).

Estimation. The final models were run with 500 random starts and 50 final stage optimizations. The minimum convergence criterion was set at 0.0001, which is the default for Mplus. Although we continued to have local maxima, the results were consistent with the prior models we ran. It is not uncommon for latent class models to have local maxima (Lanza et al., 2003; Snyder & Medeiros, 2013). One factor that likely contributed to the local maxima was that few emerging adults reported stealing something worth more than $50, and for the fighting and substance-use class, the conditional probability of stealing something over $50 approached zero.

Table 3 presents the model fit and usefulness indices for 1- to 7-class solutions. The top row indicates the number of classes in the model. Consistent with the study's first hypothesis, four distinct classes chosen based on a sufficient model fit, and the substantive meaning of each class (Nylund et al., 2007). For the BIC, the BIC SSA and the AIC the 4-class model was chosen because plots of the seven models indicated that the most substantial decline in slope had occurred by the fourth class, afterwards the slope flattened out, even though the lowest values for these fit statistics were found in the seventh class. The 2- and 3-class LRT values were significant, but these results were not consistent with the other fit statistics. The entropy values for the 5- and 6-class models were the highest. Instead of comparing solutions with differing numbers of classes, the entropy provides a measure of how "cleanly" cases can be classified into classes. The entropy value can range between 0 and 1, with higher values indicating more certainty in classification. It is important to note a lack of consensus among measures of fit is not uncommon (Snyder & Medeiros, 2013). Thus, the number of classes is based on the majority of fit indices and the interpretability of the classes as indicated by the item probabilities patterns (Collins & Lanza, 2010).

Table 3
Indicators of Fit with One Thru Seven Latent Classes by Gender

	1	2	3	4	5	6	7
LL	-57400.35	-51703.09	-50266.56	**49822.64**	-49434.84	-49221.50	-49103.55
BIC	114942.42	103699.06	100977.15	**100240.48**	99616.03	99340.52	99255.77
BIC SSA	114894.75	103600.54	100827.79	**100040.28**	99364.97	99038.62	98903.03
AIC	114830.71	103468.18	100627.11	**99771.29**	99027.67	98633.01	98429.09
LRT		11319.64	1305.96	**474.70**	365.72	263.93	234.36
P value		0.000	0.000	**0.501**	0.204	0.227	0.424
Entropy		0.785	0.769	**0.807**	0.817	0.817	0.786

***Note*.** **LL** = Log Likelihood*;* **BIC** = Bayesian Information Criteria; **BIC SSA** = sample-size-adjusted BIC; **AIC** = Akaike Information Criteria; **LRT** = Lo-Mendell Rubin Test. Bold font numbers indicate the 3-class model is chosen for males, and the 4-class model is chosen for females.

Figure 2 shows the probabilities of engaging in illegal and substance-use behaviors after relaxing conditional independence. The following pairs of variables violated the conditional independence assumption: (a) *sick or threw up after drinking* and *problems with your friends because you had been drinking*; and (b) *threatened to use a weapon to get something from someone* and *used a weapon in a fight*.

Behaviors clustered into the following four classes:

1. The **illegal and substance-use behaviors class** (5.33%) consisted of members who had fairly high probabilities of engaging in a variety of illegal and substance-use behaviors.

2. The **fighting and substance-use class** (5.24%) comprised individuals with the highest risk of fighting behaviors and high risks of substance-use behaviors

3. The **substance use class** (28.30%) consisted of individuals who used substances and engaged in few illegal behaviors.

4. The **normative class** (61.12%) members were unlikely to engage in either illegal or substance-use behaviors.

The results from the models with relaxed conditional independence did not differ substantively from the models that did not relax conditional independence. The class structures remained the same and the item response rates did not fluctuate significantly. Therefore, the 3-step method was appropriate for including predictor variables. Mplus 7 does not allow the 3-step method to relax conditional independence. Next, the predictors were added to the model following the 3-step method. The results in the form of odds ratios (ORs) and 95% confidence intervals are presented in Table 4. The normative latent class served as the referent.

Members of the illegal/substance-use class as well as the members of the fighting/substance-use class were more likely to be younger, male, Black, and less educated than members of other classes. Substance-use class members were more likely to be younger, less educated, and less likely to be Black.

Individuals who reported physical abuse had increased risk of membership in the illegal class, fighting class, and substance-use class. Specifically, those with a history of physical abuse had nearly 3 times greater likelihood of illegal class membership, 2.94 times greater likelihood of fighting class membership, and nearly 2 times greater likelihood of substance-use use class membership.

In addition, risk of membership in these three classes was higher for respondents who had friends who used substances. Respondents whose Wave 1 friends smoked, drank, or used marijuana had a higher risk of illegal class membership. Respondents who had friends at Wave 1 who drank or smoked had higher risk of membership in both the fighting and substance-use classes. Having friends during Wave 1 who smoked cigarettes or drank alcohol increased the risk of both fighting and substance use class. At Wave 3, being a gang member lowered the risk of membership in the illegal and substance use class, but was not significantly related to membership in the other classes.

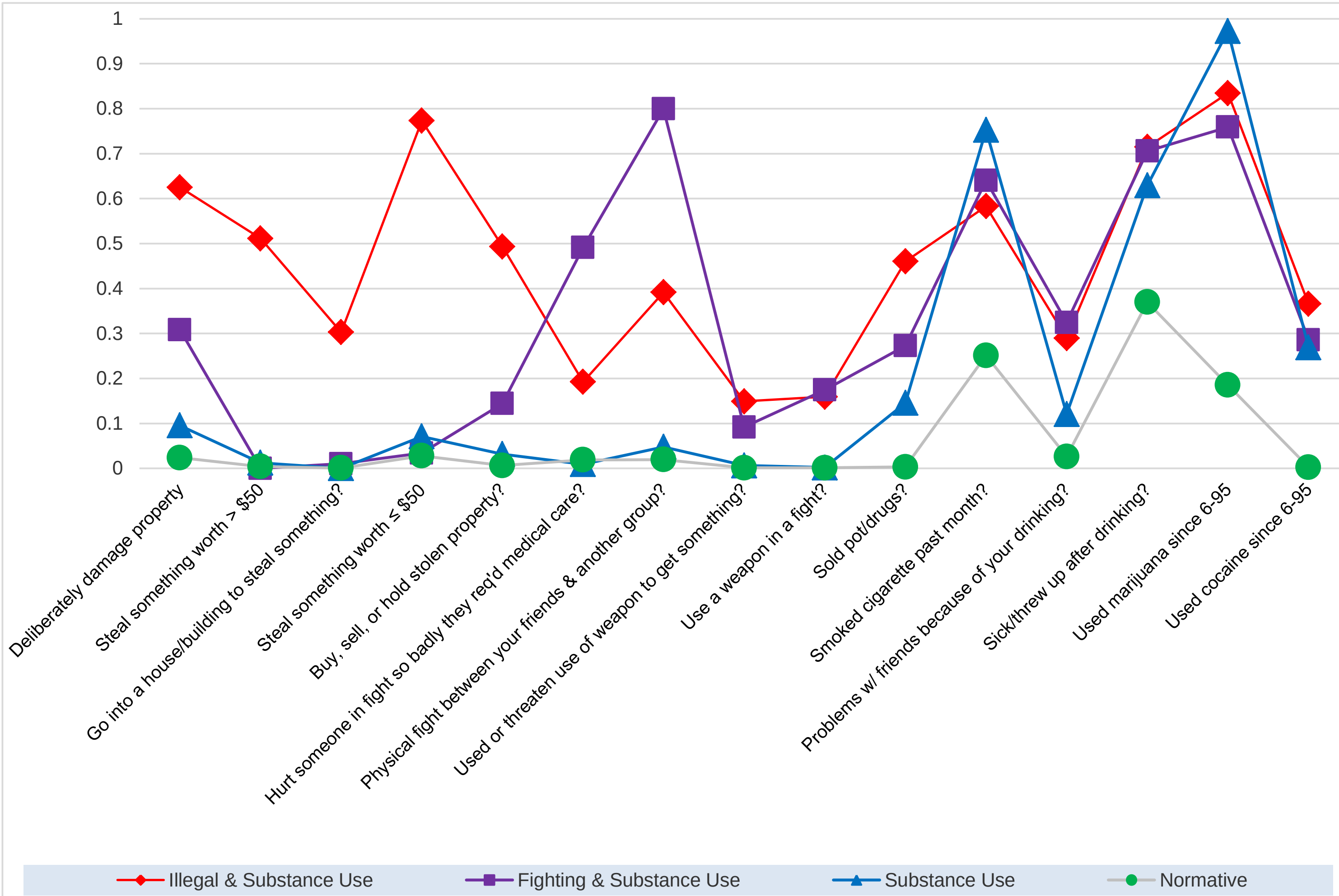

Figure 2. *Four-class model with relaxed conditional independence*

Note. Illegal and substance-use behaviors were reported at Wave 3. Unless otherwise indicated the behaviors occurred within the past 12 months

Table 4

Odds Ratios Comparing Illegal Behavior and Substance-Use Classes with Normative Class

	Illegal & Sub. Use (c1) vs. Normative (c4)		Fighting & Sub. Use (c1) vs. Normative (c4)		Substance Use (c3) vs. Normative (c4)	
	Odds	95% CI	Odds	95% CI	Odds	95% CI
Male	4.71***	[3.42, 6.50]	6.87***	[4.49, 10.51]	1.22	[0.99, 1.51]
Hispanic	1.02	[0.63, 1.63]	1.18	[0.75, 1.87]	0.70*	[0.50, 0.97]
Black	1.67*	[1.11, 2.52]	1.84*	[1.21, 2.79]	0.36***	[0.25, 0.53]
Age	0.46***	[0.39, 0.56]	0.64***	[0.52, 0.78]	0.82***	[0.74, 0.92]
Education	0.86	[0.73, 1.00]	0.70**	[0.56, 0.86]	0.84**	[0.74, 0.95]
Physical abuse	2.77***	[1.56, 4.92]	3.16***	[1.81, 5.50]	2.09***	[1.39, 3.14]
# Friends smoke	1.15	[0.97, 1.37]	1.37***	[1.15, 1.62]	1.49***	[1.35, 1.64]
# Friends drink	2.55***	[2.16, 3.02]	2.70***	[2.21, 3.29]	2.35***	[2.09, 2.64]
# Friends marijuana	1.78***	[1.52, 2.10]	1.82***	[1.56, 2.13]	1.69***	[1.53, 1.85]
Gang member	0.55*	[0.35, 0.86]	1.03	[0.67, 1.57]	0.97	[0.74, 1.28]

* $p < 0.05$, ** $p<0.01$, *** $p<0.001$

Table 5

Odds Ratios of Direct Effects Between Peer Covariates and Latent Class Indicators

	Odds	95% CI
Medical care needed after fight regressed on Gang member	2.29*	[1.15, 4.55]
Group fight regressed on Gang member	1.97	[0.84, 4.64]
Used/threaten weapon regressed on Gang member	1.53	[0.85, 2.77]
Used weapon in fight regressed on Gang member	2.50**	[1.25, 4.99]
Sold drugs regressed on # friends smoke	1.14	[1.00, 1.30]
Sold drugs regressed on # friends drink	1.47***	[1.27, 1.70]
Sold drugs regressed on # friends use marijuana	1.27***	[1.12, 1.43]
Smoked cigarettes regularly regressed on # friends smoke	1.95***	[1.80, 2.11]
Smoked cigarettes regularly regressed on # friends drink	1.41***	[1.31, 1.52]

Table 5
Odds Ratios of Direct Effects Between Peer Covariates and Latent Class Indicators

	Odds	95% CI
Smoked cigarettes regularly regressed on		
# friends use marijuana	1.39***	[1.28, 1.50]
Alcohol friend problems regressed on		
# friends smoke	1.02	[0.91, 1.13]
Alcohol friend problems regressed on		
# friends drink	1.60***	[1.38, 1.85]
Alcohol friend problems regressed on		
# friends use marijuana	1.10	[0.99, 1.22]
Sick/threw up after drinking regressed on		
# friends smoke	0.92*	[0.86, 1.00]†
Sick/threw up after drinking regressed on		
# friends drink	1.70***	[1.57, 1.84]
Sick/threw up after drinking regressed on		
# friends use marijuana	1.05	[0.98, 1.13]
Used marijuana during past 7 years regressed on		
# friends smoke	1.22***	[1.11, 1.35]
Used marijuana during past 7 years regressed on		
# friends drink	2.93***	[2.56, 3.36
Used marijuana during past 7 years regressed on		
# friends use marijuana	1.74***	[1.56, 1.95]

* $p < 0.05$, ** $p<0.01$, *** $p<0.001$
† This value was below 1.00 prior to rounding.

Post-hoc analyses of direct effects. Based both on the results we found and the literature we cited we decided to explore whether there were direct effects between our covariates for peer influences and latent class indicators. We regressed the latent class indicators on the covariates, which provided regression estimates that indicated the strength of the relationship. The results from these analyses are provided in Table 5. Within Table 5, a significant effect means that the coefficient is sufficiently large relative to its standard error, which allows us to differentiate a coefficient from one in an odds ratio (or no difference). The values of the coefficients specify the strength of the covariates to the class indicators after accounting for the association between the class indicator and the class. For example, needing medical care after a fight is associated with gang membership beyond any relationship between belonging to a gang and class membership. Strong relationships between the class indicators and the predictor variables indicate latent class membership does not capture all of the relevant variability in the indicators. Substantively important relationships between covariates and class indicators suggest that the class model does not tell the full story.

Discussion

The purpose of this study was to begin to fill gaps in the existing literature by exploring patterns of illegal behaviors and substance use with a national sample of emerging adults. This study focused on the following four hypotheses:

- **Hypothesis 1. Emerging adults will cluster into distinct subpopulations.**

Consistent with prior literature and the study's first hypothesis, the results showed the patterns of illegal behaviors and substance use clustered into four classes. In addition, this study demonstrated that the largest class included individuals who engaged in few illegal or substance-use behaviors (Shin et al., 2010; Cleveland et al., 2010; Odgers et al., 2008; Lynskey et al., 2006; Brownfield & Sorenson, 1987).

- **Hypothesis 2. A history of physical abuse will elevate the risk for class membership in the most severe illegal and substance-use behavior classes.**

This hypothesis was supported by findings that showed a history of physical abuse nearly tripled the likelihood of illegal class membership. In addition, study results indicated that members of the fighting and the substance use classes were more likely to have been physically abused. These results are consistent with studies that have linked a history of physical abuse to both illegal behaviors (Widom, 1989; Widom & Maxfield, 2001) and substance use (Widom & Hiller-Sturmhofel, 2001; Widom et al., 2006).

- **Hypothesis 3. Peer influences during adolescence will elevate the risk for class membership in the most severe illegal and substance-use behavior classes.**

Consistent with social learning theory literature, the study's third hypothesis was confirmed. Similar to findings of other studies (CDC, 1994; Urberg et al., 2003), the present study showed that respondents who had friendships at Wave 1 with peers who smoked, drank, or used marijuana elevated the respondents' likelihood of illegal class membership.

Because this study distinguished fighting behaviors from a range of other illegal behaviors, the findings clearly delineated how adolescent friendships with peers who drank or smoked elevated the respondents' risk of engaging in fighting behaviors. Conversely, the study showed gang membership decreased the likelihood that an emerging adult would be in the fighting and substance-use classes. These findings differ somewhat from the findings of both Gatti et al. (2005) and Battin et al. (1998), which predicted that gang membership would increase illegal behaviors generally, while our study found a reduced risk of illegal behaviors among gang members. It may be that emerging adults who are gang members have become established in the hierarchy of their gangs and no longer have to demonstrate their allegiance by stealing or damaging property. Future studies should explore the underlying mechanisms that reduce the risk of illegal behaviors among emerging adults who are gang members.

- **Hypothesis 4. Emerging adults who are younger, male, and Black will be at greater risk of being in the class with the most severe illegal and substance-use behaviors.**

Although the study findings are in accord with those prior studies that applied social learning theory and found problematic behaviors were most common among younger (Agnew, 2003; Sampson & Laub, 2005) and less-educated individuals (Akers, 2009), these findings are counter to those of studies focused on problematic behaviors among college students (White et al., 2006; Arnett, 1994). One explanation of this discord might be that a large, diverse sample made it difficult to detect problem behaviors among college students because relatively few college students engage in problematic behaviors. We also found a lower risk of substance use among Black emerging adults, suggesting support for the crossover effect (Arnett & Brody, 2009). However, additional research is needed to verify this claim. In particular, future studies should follow participants from emerging adulthood until they are older than 35 years to determine the long-term influence of peer relationships on behavior. This is particularly important because at age 35 Black substance use surpasses the rates of Whites and Hispanics (Arnett & Brody, 2009).The study findings were also in line with the cycle of violence theory in that the results showed membership in the most severe classes was associated with physical abuse. However, this finding differs from that of Shin et al.'s (2010) study that investigated the association with mild or moderate physical abuse. This disparity in findings suggests a dosage effect might exist for physical abuse wherein more severe physical abuse is associated with problematic behaviors whereas mild to moderate abuse is not.

A key limitation of this study is its focus on outcomes at Wave 3, creating an artificial viewpoint that is limited in time. An additional study limitation was the absence of certain key variables (e.g., a wider range of substance-abuse related variables) that would have been informative. For example, the study findings might be of greater value if it was also known with whom the emerging adult used drugs and how he or she was introduced to the drugs. Having more information about respondents' patterns of marijuana use (i.e., frequency, intensity, duration) would have added interesting and potentially valuable information. Last, including variables to explore protective factors in peer relationships would be useful and informative. Such protective factors might include having peers who perform well in school, having peers who participate in church or civic groups, or having peers who volunteer with community agencies. As the results of the post-hoc analyses suggest, the presence of some of these variables might have been able to provide a fuller explanation of the data than the current modeling.

Despite these limitations, this study has several strengths. First, the findings illuminate two enduring influences on emerging adults' patterns of illegal behavior and substance-use behaviors: physical abuse and peers. Second, the analyses are informative about areas of differences between women and men. Third, rather than focusing on a small geographic region, this study used a large nationally representative data set, making the results generalizable to emerging adults across the country. Fourth, the study underscores the importance of exploring interrelationships of illegal and substance-use behaviors.

Implications

As the study findings suggest, the occurrence and interrelationships of illegal behaviors and substance use among emerging adults is a complex problem. However, steps to decrease risk of these behaviors can be taken in the spheres of research, practice, and policy.

Future studies should focus on the enduring effects adolescent friendships can have on a range of maladaptive behaviors, including Internet addiction, compulsive gambling, and obesity. Further, more research needs to examine if a dosage effect exists for child physical abuse and at what developmental stage child physical abuse begins to influence externalizing behaviors and substance use behaviors. Likewise, future studies should examine the underlying mechanisms that increase susceptibility to illegal and fighting behaviors among emerging adults who are male or Black. Future studies should also explore if variables included in this study predict illegal behaviors and substance use among different populations and different stages of development. For example, it would be interesting to better understand the influence of physical abuse and peer deviance on patterns of delinquency among adolescents involved in the child welfare system. In addition, qualitative studies are needed to better understand the ways in which child physical abuse fosters illegal and substance-use behaviors. Specifically, it would be useful to understand how the family dynamics associated with physical abuse influence emerging adults' decisions to engage in illegal and substance-use behaviors.

From a practice perspective, social work practitioners working with emerging adults who have engaged in illegal behaviors should assess those clients for substance-use behaviors. Similarly, practitioners working with populations that abuse substances should assess for illegal behaviors. Moreover, social workers need to be aware that emerging adults who are male or Black have a heightened risk for engaging in illegal behaviors and should screen clients for those behaviors. Social workers who work with adolescents should ask their clients about gang involvement and whether their friends use sub-stances, including alcohol, tobacco, and marijuana. Notably, this study did not find gender-based differ-ences in substance-use patterns. Thus, it is important for practitioners working with emerging adults to ask all clients about their patterns of substance use. On the other hand, because Black emerging adults have a relatively low risk of substance use, social workers should consider the developmental stage of emerging adulthood as an intervention point for substance use/abuse prevention efforts.

The study findings also have implications for policy. The findings suggest the importance of developing policies that can provide early intervention to help adolescents make positive choices regarding peer affiliations. In addition, this study found higher risks for engaging in illegal behavior among male and Black emerging adults, and thus, underscored the urgent need for policies targeting preventive intervention toward Black youth to address the racial disparity and disproportionate representation of Blacks in the U.S. criminal justice system. Relatedly, policies should be developed to focus substance-use prevention efforts on Black emerging adults because such efforts are likely to be more effective during this developmental period, which has a low risk of substance use among Blacks. Last, social workers and policy makers need to collaborate on policies to address child physical abuse prevention efforts as a means to reduce later illegal and substance-use behaviors among emerging adults.

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Appendix: Mplus Code

```
Title: 4 class solution that examines conditional independence

! Explanation marks are used for comments.

! This code was also used for testing two halves of the randomly split sample to ensure that the class structure was
! consistent.

Data:
  File is c:\data\ peers.dat ;
Variable:
  Names are
    region GSWGT3 GSWGT3_2 pr1_3d pr2_3d pr3_3d pr4_3d pr5_3d ft1_3d ft2_3d
    ft3_3d wp1_3d wp2_3d wp3_3d dr1_3d dr2_3d dr3_3d dr5_3d dr9_3d dr14_3d
    dr15_3d dr16_3d dr17_3d dr18_3d dr29_3d dr23_3d hispanic white_o black_o
    t1nhood1 t3physab t3gang z2t3auf z2t3euf id z2t1fsf z2t1fdf z2t1fmf
    dr6_3d;
  Missing are all (-9999) ;

! Usevariables indicates all of the variables used in the analysis.

 USEVARIABLES =  pr1_3d ! Deliberately damage property that didn't belong to you
                     pr2_3d !  Steal something worth more than $50
                     pr3_3d !  Go into a house or building to steal something
                     pr4_3d !  Steal something worth less than $50
                     pr5_3d !  Buy, sell, or hold stolen property
                     ft1_3d !   Hurt someone badly enough in a physical fight that he or she needed
                     ft2_3d !   Fight between a group of your friends was against another group
                     wp1_3d ! Use or threaten to use a weapon to get something from someone
                     wp3_3d ! Use a weapon in a fight
                     dr1_3d !  Sold pot drugs
                     dr6_3d !  Smoked cigarette past month
                     dr15_3d ! Dichotomous problems with your friend s because you had been drinking.
                     dr18_3d ! Sick/threw up after drinking
                     dr29_3d ! Used marijuana since 6-95
                     dr23_3d;! Used cocaine since 6-95;

!! This looks at a 4 class solution
!   The same code is used with classes 1, 2, 3, 4, 5, 6, and 7, but the number in parentheses is changed to indicate the
!   class being examined
CLASSES =c(4);
Stratification is region;
Cluster is t1nhood1;
Weight is gswgt3_2;

CATEGORICAL ARE  pr1_3d ! Deliberately damage property that didn't belong to you
                     pr2_3d !  Steal something worth more than $50
                     pr3_3d !  Go into a house or building to steal something
                     pr4_3d !  Steal something worth less than $50
                     pr5_3d !  Buy, sell, or hold stolen property
                     ft1_3d !   Hurt someone badly enough in a physical fight that he or she needed
                     ft2_3d !   Fight between a group of your friends was against another group
                     wp1_3d ! Use or threaten to use a weapon to get something from someone
                     wp3_3d ! Use a weapon in a fight
```

```
                dr1_3d !  Sold pot drugs
                dr6_3d !  Smoked cigarette past month
                dr15_3d ! Dichotomous problems with your friend s because you had been drinking.
                dr18_3d ! Sick/threw up after drinking
                dr29_3d ! Used marijuana since 6-95
                dr23_3d;! Used cocaine since 6-95;

!!!!! ID VARIABLE
idvariable =id;

ANALYSIS: TYPE = MIXTURE complex;
STARTS = 500 50;
ALGORITHM is INTEGRATION;
integration = montecarlo;

OUTPUT:
! Tech11 is the LO-MENDELL-RUBIN statistic.
        tech11;
!Tech8 provides the output for the EM algorithm.
        tech8;
!Tech10 provides the results of the conditional independence tests
        tech10;

! Savedata is used to output data into a text file that can be read into Stata or another program.
savedata:
        save = cprob;
        file = 4c_ Peers.txt;
        format=free;
```

```
Title: 4 class solution that accounts for conditional independence among dr15_3d & dr18_3d; dr1_3d & dr23_3d &
pr2_3d & pr4_3d

! Please note that controlling for conditional independence is time consuming and can affect the stability of your
! model.
! Thus, we first ran a model was run with just dr15_3d & dr18_3d
! Then we added dr1_3d & dr23_3d to the second model
! This is our third model.

Data:
  File is c:\data\peers.dat ;
Variable:
  Names are
     region GSWGT3 GSWGT3_2 pr1_3d pr2_3d pr3_3d pr4_3d pr5_3d ft1_3d ft2_3d
     ft3_3d wp1_3d wp2_3d wp3_3d dr1_3d dr2_3d dr3_3d dr5_3d dr9_3d dr14_3d
     dr15_3d dr16_3d dr17_3d dr18_3d dr29_3d dr23_3d hispanic white_o black_o
     t1nhood1 t3physab t3gang z2t3auf z2t3euf id z2t1fsf z2t1fdf z2t1fmf
     dr6_3d;
  Missing are all (-9999) ;

! Usevariabels indicates all of the variables used in the analysis.
 USEVARIABLES =  pr1_3d ! Deliberately damage property that didn't belong to you
                    pr2_3d !  Steal something worth more than $50
                    pr3_3d !  Go into a house or building to steal something
                    pr4_3d !  Steal something worth less than $50
                    pr5_3d !  Buy, sell, or hold stolen property
                    ft1_3d !   Hurt someone badly enough in a physical fight that he or she needed
                    ft2_3d !   Fight between a group of your friends was against another group
                    wp1_3d ! Use or threaten to use a weapon to get something from someone
                    wp3_3d ! Use a weapon in a fight
                    dr1_3d !  Sold pot drugs
                    dr6_3d !  Smoked cigarette past month
                    dr15_3d ! Dichotomous problems with your friend s because you had been drinking.
                    dr18_3d ! Sick/threw up after drinking
                    dr29_3d ! Used marijuana since 6-95
                    dr23_3d;! Used cocaine since 6-95;

!! This looks at a 4 class solution
CLASSES =c(4);
Stratification is region;
Cluster is t1nhood1;
Weight is gswgt3_2;

CATEGORICAL ARE   pr1_3d ! Deliberately damage property that didn't belong to you
                    pr2_3d !  Steal something worth more than $50
                    pr3_3d !  Go into a house or building to steal something
                    pr4_3d !  Steal something worth less than $50
                    pr5_3d !  Buy, sell, or hold stolen property
                    ft1_3d !   Hurt someone badly enough in a physical fight that he or she needed
                    ft2_3d !   Fight between a group of your friends was against another group
                    wp1_3d ! Use or threaten to use a weapon to get something from someone
                    wp3_3d ! Use a weapon in a fight
                    dr1_3d !  Sold pot drugs
                    dr6_3d !  Smoked cigarette past month
                    dr15_3d ! Dichotomous problems with your friend s because you had been drinking.
                    dr18_3d ! Sick/threw up after drinking
```

```
                              dr29_3d ! Used marijuana since 6-95
                              dr23_3d;! Used cocaine since 6-95;
!! ID VARIABLE
idvariable =id;

ANALYSIS: TYPE = MIXTURE complex;
STARTS = 500 50;
ALGORITHM is INTEGRATION;
integration = montecarlo;

MODEL:
! The whole model
%Overall%
                              f1 BY  dr15_3d@0 dr18_3d@0;
                              f1@1; [f1@0];
                              f2 BY  wp1_3d@0 wp3_3d@0;
                              f2@1; [f2@0];
 %c#1%
                              [pr1_3d$1 !
                              pr2_3d$1 !
                              pr3_3d$1 !
                              pr4_3d$1 !
                              pr5_3d$1 !
                              ft1_3d$1 !
                              ft2_3d$1 !
                              wp1_3d$1 !
                              wp3_3d$1 !
                              dr1_3d$1 !
                              dr6_3d$1 !
                              dr15_3d$1
                              dr18_3d$1
                              dr29_3d$1
                              dr23_3d$1];

                              f1 BY  dr15_3d@1 dr18_3d@0;
                              f1@1; [f1@0];
                              f2 BY  wp1_3d@1 wp3_3d@0;
                              f2@1; [f2@0];
 %c#2%
                              [pr1_3d$1 !
                              pr2_3d$1 !
                              pr3_3d$1 !
                              pr4_3d$1 !
                              pr5_3d$1 !
                              ft1_3d$1 !
                              ft2_3d$1 !
                              wp1_3d$1 !
                              wp3_3d$1 !
                              dr1_3d$1 !
                              dr6_3d$1 !
                              dr15_3d$1
                              dr18_3d$1
                              dr29_3d$1
                              dr23_3d$1];
```

```
                    f1 BY  dr15_3d@1 dr18_3d@0;
                    f1@1; [f1@0];
                    f2 BY  wp1_3d@1 wp3_3d@0;
                    f2@1; [f2@0];

 %c#3%
                    [pr1_3d$1 !
                    pr2_3d$1 !
                    pr3_3d$1 !
                    pr4_3d$1 !
                    pr5_3d$1 !
                    ft1_3d$1 !
                    ft2_3d$1 !
                    wp1_3d$1 !
                    wp3_3d$1 !
                    dr1_3d$1 !
                    dr6_3d$1 !
                    dr15_3d$1
                    dr18_3d$1
                    dr29_3d$1
                    dr23_3d$1];

                    f1 BY  dr15_3d@1 dr18_3d@0;
                    f1@1; [f1@0];

 %c#4%
                    [pr1_3d$1 !
                    pr2_3d$1 !
                    pr3_3d$1 !
                    pr4_3d$1 !
                    pr5_3d$1 !
                    ft1_3d$1 !
                    ft2_3d$1 !
                    wp1_3d$1 !
                    wp3_3d$1 !
                    dr1_3d$1 !
                    dr6_3d$1 !
                    dr15_3d$1
                    dr18_3d$1
                    dr29_3d$1
                    dr23_3d$1];

                    f1 BY  dr15_3d@1 dr18_3d@0;
                    f1@1; [f1@0];

OUTPUT:
! Tech11 is the LO-MENDELL-RUBIN statistic.
        tech11;
!Tech8 provides the output for the EM algorithm.
        tech8;
!Tech10 provides the results of the conditional independence tests
        tech10;
 savedata:
        save = cprob;
        file = 4c_CI_Peers.txt;
        format=free;
```

```
Title: Peers & Physical Abuse: 4 Classes with Auxiliary variables

 Data:
  File is 2013_8_31_use3_peers.dat ;
 Variable:
  Names are
     region GSWGT3 GSWGT3_2 pr1_3d pr2_3d pr3_3d pr4_3d pr5_3d ft1_3d ft2_3d
     ft3_3d wp1_3d wp2_3d wp3_3d dr1_3d dr2_3d dr3_3d dr5_3d dr9_3d dr14_3d
     dr15_3d dr16_3d dr17_3d dr18_3d dr29_3d dr23_3d male hispanic white_o
     black_o t1nhood1 t3physab t3gang z2t3au3 z2t3eu3 id z2t1fs3 z2t1fdu3
     z2t2fm3 dr6_3d;
  Missing are all (-9999) ;

  ! Usevariabels indicates all of the variables used in the analysis.
   USEVARIABLES =    pr1_3d
                     pr2_3d
                     pr3_3d
                     pr4_3d
                     pr5_3d
                     ft1_3d
                     ft2_3d
                     wp1_3d
                     wp3_3d
                     dr1_3d
                     dr6_3d
                     dr9_3d
                     dr14_3d
                     dr15_3d
                     dr18_3d
                     dr29_3d
                     dr23_3d

                     !!!!!!!!!!!!!!!!!!!!!! COVARIATES !!!!!!!!!!!!!!!!!!!!!!!!!
                     male
                     hispanic ! Hispanic or Latino origin W1
                     black_o ! Black only W1
                     ! white_o ! White only W1
                     z2t3au3
                     z2t3eu3
                     t3physab
                     z2t1fs3
                     z2t1fdu3
                     z2t2fm3
                     t3gang;

!! This looks at a 4 class solution
CLASSES =c(4);
Stratification is region;
Cluster is t1nhood1;
Weight is gswgt3_2;

CATEGORICAL ARE      pr1_3d
                     pr2_3d
                     pr3_3d
                     pr4_3d
                     pr5_3d
```

```
                    ft1_3d
                    ft2_3d
                    wp1_3d
                    wp3_3d
                    dr1_3d
                    dr6_3d
                    dr9_3d
                    dr14_3d
                    dr15_3d
                    dr18_3d
                    dr29_3d
                    dr23_3d;

AUXILIARY = (R3STEP) male
                    hispanic
                    black_o
                    z2t3au3
                    z2t3eu3
                    t3physab
                    z2t1fs3
                    z2t1fdu3
                    z2t2fm3
                    t3gang;

!!!!! ID VARIABLE
idvariable =id;

ANALYSIS: TYPE = MIXTURE complex;
! increase number of random starts - they default at 10;
STARTS =500 50;
PROCESS=8(STARTS);
!Processors=2;
! ALGORITHM is INTEGRATION;
!integration = montecarlo;

MODEL:
%Overall%

! Start values were taken from the final model relaxing conditional independence.
! Please note that we changed the order of the classes to match the order we wanted.

%c#1%

! Latent class 1 was latent class 2

                    [PR1_3D$1*-0.512
                     PR2_3D$1*-0.046
                     PR3_3D$1* 0.834
                     PR4_3D$1*-1.226
                     PR5_3D$1* 0.026
                     FT1_3D$1* 1.434
                     FT2_3D$1* 0.441
                     WP1_3D$1* 1.743
                     WP3_3D$1* 1.663
                     DR1_3D$1* 0.159
                     DR6_3D$1*-0.335
```

```
DR15_3D$1*0.897
DR18_3D$1*-0.918
DR29_3D$1*-1.618
DR23_3D$1*0.550];

%c#2%

Latent class 2 was latent class 4

[PR1_3D$1* 0.808
PR2_3D$1
PR3_3D$1* 4.573
PR4_3D$1* 3.346
PR5_3D$1* 1.780
FT1_3D$1* 0.035
FT2_3D$1*-1.384
WP1_3D$1* 2.289
WP3_3D$1* 1.555
DR1_3D$1* 0.981
DR6_3D$1*-0.576
DR15_3D$1*0.734
DR18_3D$1*-0.875
DR29_3D$1*-1.147
DR23_3D$1*0.916];

%c#3%

! Latent class 3 was latent class 3

[PR1_3D$1* 2.249
PR2_3D$1* 4.377
PR3_3D$1* 8.376
PR4_3D$1* 2.569
PR5_3D$1* 3.411
FT1_3D$1* 4.656
FT2_3D$1* 2.988
WP1_3D$1* 5.020
WP3_3D$1* 6.186
DR1_3D$1* 1.771
DR6_3D$1*-1.113
DR15_3D$1*1.984
DR18_3D$1*-0.529
DR29_3D$1*-3.580
DR23_3D$1*1.001];

%c#4%

! Latent class 4 was latent class 1

[PR1_3D$1* 3.712
PR2_3D$1* 5.455
PR3_3D$1* 6.966
PR4_3D$1* 3.553
PR5_3D$1* 5.035
FT1_3D$1* 3.938
FT2_3D$1* 3.904
```

```
                    WP1_3D$1* 6.572
                    WP3_3D$1* 6.558
                    DR1_3D$1* 5.707
                    DR6_3D$1* 1.092
                    DR15_3D$1*3.615
                    DR18_3D$1*0.533
                    DR29_3D$1*1.480
                    DR23_3D$1*6.000];


OUTPUT:
! Tech11 is the LO-MENDELL-RUBIN statistic.
        tech11;
!Tech8 provides the output for the EM algorithm.
        tech8;
!Tech10 provides the results of the conditional independence tests
        tech10;

  savedata:
   save = cprob;
   file = 4c_All_cases_Peers_AH_Auxiliary_vars.txt;
```

```
Title: 4 Classes with covariates with a direct effect - All Cases - 15 variables - Peers

 Data:
   File is 2013_8_31_use3_peers.dat ;
 Variable:
   Names are
      region GSWGT3 GSWGT3_2 pr1_3d pr2_3d pr3_3d pr4_3d pr5_3d ft1_3d ft2_3d
      ft3_3d wp1_3d wp2_3d wp3_3d dr1_3d dr2_3d dr3_3d dr5_3d dr9_3d dr14_3d
      dr15_3d dr16_3d dr17_3d dr18_3d dr29_3d dr23_3d male hispanic white_o
      black_o t1nhood1 t3physab t3gang z2t3au3 z2t3eu3 id z2t1fs3 z2t1fdu3
      z2t2fm3 dr6_3d;
   Missing are all (-9999) ;

   ! Usevariabels indicates all of the variables used in the analysis.
    USEVARIABLES =   pr1_3d
                            pr2_3d
                            pr3_3d
                            pr4_3d
                            pr5_3d
                            ft1_3d
                            ft2_3d
                            wp1_3d
                            wp3_3d
                            dr1_3d
                            dr6_3d
                            dr9_3d
                            dr14_3d
                            dr15_3d
                            dr18_3d
                            dr29_3d
                            dr23_3d

                  !!!!!!!!!!!!!!!!!!!!!! COVARIATES !!!!!!!!!!!!!!!!!!!!!!!!!!
                            male
                            hispanic ! Hispanic or Latino origin W1
                            black_o ! Black only W1
                            z2t3au3
                            z2t3eu3
                            t3physab
                            z2t1fs3
                            z2t1fdu3
                            z2t2fm3
                            t3gang;


!! This looks at a 4 class solution
CLASSES =c(4);
Stratification is region;
Cluster is t1nhood1;
Weight is gswgt3_2;

        CATEGORICAL ARE pr1_3d
                        pr2_3d
                        pr3_3d
                        pr4_3d
                        pr5_3d
```

```
                        ft1_3d
                        ft2_3d
                        wp1_3d
                        wp3_3d
                        dr1_3d
                        dr6_3d
                        dr9_3d
                        dr14_3d
                        dr15_3d
                        dr18_3d
                        dr29_3d
                       dr23_3d;


       !!!!! ID VARIABLE (
       idvariable =id;

  ANALYSIS: TYPE = MIXTURE complex;
       STARTS =500 50;
       PROCESS=8(STARTS);
       !Processors=2;
       ! ALGORITHM is INTEGRATION;
       !integration = montecarlo;

 MODEL:
 %Overall%
                  c#1-c#2 on  male
                       hispanic ! Hispanic or Latino origin W1
                       black_o ! Black only W1
                       ! white_o ! White only W1
                       z2t3au3
                       z2t3eu3
                       t3physab
                       z2t1fs3
                       z2t1fdu3
                       z2t2fm3
                       t3gang;

! Because the covariates are measured at Wave 1 (substance use)
  ! and the latent class indicators are measured at a later time point (fighting and using drugs)
      !This will provide regression estimates that would indicate the strength of the relationship

  !  To test the direct effect between covariates and latent class indicators
       ! gang membership is predictive of being in group fights, hurting others in a fight
          ft1_3d on t3gang;
          ft2_3d on t3gang;
          wp1_3d on t3gang;
          wp3_3d on t3gang;
      ! Likewise, having association with others who use alcohol and drugs is strongly related with drug use.
           dr6_3d on  z2t1fs3
                       z2t1fdu3
                       z2t2fm3;
          dr9_3d on  z2t1fs3
                       z2t1fdu3
                       z2t2fm3;
          dr14_3d  on  z2t1fs3
```

```
                z2t1fdu3
                z2t2fm3;
dr15_3d on  z2t1fs3
                z2t1fdu3
                z2t2fm3;
dr18_3d on  z2t1fs3
                z2t1fdu3
                z2t2fm3;
dr29_3d on  z2t1fs3
                z2t1fdu3
                z2t2fm3;
dr23_3d on  z2t1fs3
                z2t1fdu3
                z2t2fm3;

                  %c#1%
                 ! Latent class 1 was LC2
                 PR1_3D$1*-0.512
                 PR2_3D$1*-0.046
                 PR3_3D$1* 0.834
                 PR4_3D$1*-1.226
                 PR5_3D$1* 0.026
                 FT1_3D$1* 1.434
                 FT2_3D$1* 0.441
                 WP1_3D$1* 1.743
                 WP3_3D$1* 1.663
                 DR1_3D$1* 0.159
                 DR6_3D$1*-0.335
                 DR15_3D$1*0.897
                 DR18_3D$1*-0.918
                 DR29_3D$1*-1.618
                 DR23_3D$1*0.550];

                 %c#2%
                ! Latent class 2 was LC4
                [PR1_3D$1* 0.808
                PR2_3D$1
                PR3_3D$1* 4.573
                PR4_3D$1* 3.346
                PR5_3D$1* 1.780
                FT1_3D$1* 0.035
                FT2_3D$1*-1.384
                WP1_3D$1* 2.289
                WP3_3D$1* 1.555
                DR1_3D$1* 0.981
                DR6_3D$1*-0.576
                DR15_3D$1*0.734
                DR18_3D$1*-0.875
                DR29_3D$1*-1.147
                DR23_3D$1*0.916];

                %c#3%
                ! Latent class 3 was LC3
                 [PR1_3D$1* 2.249
                PR2_3D$1* 4.377
                PR3_3D$1* 8.376
```

```
PR4_3D$1* 2.569
PR5_3D$1* 3.411
FT1_3D$1* 4.656
FT2_3D$1* 2.988
WP1_3D$1* 5.020
WP3_3D$1* 6.186
DR1_3D$1* 1.771
DR6_3D$1*-1.113
DR15_3D$1*1.984
DR18_3D$1*-0.529
DR29_3D$1*-3.580
DR23_3D$1*1.001];

    %c#4%
! Latent class 4 was LC1
 [PR1_3D$1* 3.712
 PR2_3D$1* 5.455
 PR3_3D$1* 6.966
 PR4_3D$1* 3.553
 PR5_3D$1* 5.035
 FT1_3D$1* 3.938
 FT2_3D$1* 3.904
 WP1_3D$1* 6.572
 WP3_3D$1* 6.558
 DR1_3D$1* 5.707
 DR6_3D$1* 1.092
 DR15_3D$1*3.615
 DR18_3D$1*0.533
 DR29_3D$1*1.480
 DR23_3D$1*6.000];

OUTPUT:
! Tech11 is the LO-MENDELL-RUBIN statistic.
        tech11;
!Tech8 provides the output for the EM algorithm.
        tech8;
!Tech10 provides the results of the conditional independence tests
        tech10;

 savedata:
 save = cprob;
 file = 2013_9_3_4c_All_cases_Peers_AH_direct_effects.txt;
```